NAVIGATIONAL PATH ANALYSIS OF MOBILE ROBOT IN VARIOUS ENVIRONMENTS

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Mukesh Kumar Singh

Navigational Path Analysis of Mobile Robot in Various Environments

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by

Mukesh Kumar Singh

Under the guidance of

Prof. Dayal R. Parhi

Department of Mechanical Engineering
National Institute of Technology Rourkela
Orissa (India)-769008

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Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

(*Mukesh Kumar Singh*)

Date: 16/11/2009

NATIONAL INSTITUE OF TECHNOLOGY
ROURKELA -769008, ORISSA, INDIA.

Certificate

*This is to certify that the thesis entitled, **"Navigational Path Analysis of Mobile robot in various Environment",** being submitted by Mr. Mukesh Kumar Singh to the Department of Mechanical Engineering, National Institute of Technology, Rourkela, for the partial fulfillment of award of the degree Doctor of Philosophy, is a record of bona fide research work carried out by him under my supervision and guidance.*

This thesis in my opinion, is worthy of consideration for award of the degree of Doctor of Philosophy in accordance with the regulation of the institute. To the best of my knowledge, the results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

Supervisor

Date: 16/11/2009

(*Dayal R. Parhi*)
Professor,
Department of
Mechanical Engineering
National Institute of Technology
Rourkela, Orissa, India- 769008.

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Synopsis

This dissertation describes work in the area of an autonomous mobile robot. The objective is navigation of mobile robot in a real world dynamic environment avoiding structured and unstructured obstacles either they are static or dynamic. The shapes and position of obstacles are not known to robot prior to navigation. The mobile robot has sensory recognition of specific objects in the environments. This sensory-information provides local information of robots immediate surroundings to its controllers. The information is dealt intelligently by the robot to reach the global objective (the target). Navigational paths as well as time taken during navigation by the mobile robot can be expressed as an optimisation problem and thus can be analyzed and solved using AI techniques. The optimisation of path as well as time taken is based on the kinematic stability and the intelligence of the robot controller. A successful way of structuring the navigation task deals with the issues of individual behaviour design and action coordination of the behaviours. The navigation objective is addressed using fuzzy logic, neural network, adaptive neuro-fuzzy inference system and different other AI technique. The research also addresses distributed autonomous systems using multiple robots.

The proposed research work aims to broaden the development in the area of navigational path analysis of mobile robot in various (known and unknown) environments by avoiding static as well as dynamic obstacles. This research also addresses distributed autonomous systems using multiple robots which are superior in control strategy to single mobile robots in terms of reliability, expandability, and flexibility. In contrast to a single robot system; they provide increased robustness by taking advantage of inherent parallelism and redundancy. Research in autonomous multi-robot systems often focuses on mechanisms to enhance the efficiency of the group through some form of cooperation among the individual agents. An intelligent controller enables the robot to cope with its real world environment. This research is related to design of an intelligent controller for single as well as multiple mobile robots using AI techniques (i.e. Fuzzy, neural, adaptive neuro-fuzzy, heuristic rule base network) so that mobile robot able to navigate in real word dynamic environments. The current investigation focuses on optimisation of robot path as well as time taken during navigation to reach the specified targets by avoiding static as well as dynamic obstacles.

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Left-obs	=	Left obstacle distance
Right-obs	=	Right obstacle distance
Front-obs	=	Front obstacle distance
Head-ang	=	Heading angle
Tar-ang	=	Target angle
Left-v	=	Velocity of left wheel
Right-v	=	Velocity of right wheel
α	=	Angle between local coordinate x-axis to robot reference frame
β	=	Angle of the wheel plane relative to the chassis
θ	=	Angle of rotation w.r.t. global coordinate
P	=	Position in polar coordinates
R	=	Radius of the wheel
V	=	Linear velocity
ω	=	Angular velocity
t	=	Time taken by a robot to move from a distance
K	=	Control matrix
w	=	Axel length (left and right driving wheels distance)
C	=	Center of gravity point of the mobile robot
V_t	=	Linear tangential velocity
V_r	=	Linear velocity of right wheel
V_l	=	Linear velocity of left wheel
ω_t	=	Angular tangential velocity
q	=	The position of global coordinate frame
SA	=	Steering angle of the robot
M(q)	=	A symmetric, positive definite inertia matrix $\in R^{3nx3n}$
τ_r	=	Torque of right wheel
τ_l	=	Torque of left wheel
λ	=	Vector of Lagrange multipliers
μ	=	Fuzzy membership function

z	=	Centroid distance of the firing area
Med	=	Medium
$y_1^{\{1\}}$	=	Left obstacle distance from the robot
$y_2^{\{1\}}$	=	Front obstacle distance from the robot
$y_3^{\{1\}}$	=	Right obstacle distance from the robot
$y_4^{\{1\}}$	=	Target bearing of the robot
$\theta_{desired}$	=	Desired output from the neural network
θ_{actual}	=	Actual output from the neural network
f(.)	=	Activation function
W_i^j	=	Weight of the neuron connection from i in layer j
δ	=	Error gradient
$a_g, b_g,$ and c_g	=	The parameters for the fuzzy membership function
L	=	Layer of the network
PN	=	Petri net structure
ρ	=	Distance between the center of the robot's wheel axel and the target position

1 Introduction

The work described in this thesis has been carried out in the context of the navigation of various environments with mobile robots. This chapter introduces the basic concept and an overview of the research areas concerning the work carried out in this thesis. In the first part background information and motivation of research has been discussed and the aims and objective of the research have been discussed in the second part. An outline of current research work has been explained in the third part of this chapter.

1.1 Background and Motivation

Current research and development of mobile robot have attracted the attention of researchers in the areas of engineering, computer science, biology, mining and others. Mobile robots have a high potential in several applications. These include automatic freeway driving, guidance of the blind and disabled, explorations of dangerous regions and mechanical parts transfer in flexible assembly system. Progress in the field of mobile robot navigation has been slower than might have been expected from the excitement and relatively rapid advances of the early days of research. Systems where a robot is acting independently in complicated surroundings have often been proven only in very limited trials, or have not produced actions which could be thought of as particularly.

Autonomous mobile robots are intelligent agents which can perform desired tasks in various (known and unknown) environments without continuous human guidance. Many kinds of robots are autonomous to some degree. One important area of robotics research is to enable the robot to cope with its environment whether this is on land, underwater, in the air, underground or in space. A fully autonomous robot in the real world has the ability to:

- Gain information about the environment.
- Travel from one point to another point, without human navigation assistance.
- Avoid situations that are harmful to people, property or itself.
- Repair itself without outside assistance.

A robot may also be able to learn autonomously. Autonomous learning includes the ability to:

- Learn or gain new capabilities without outside assistance.
- Adjust strategies based on the surroundings.
- Adapt to surroundings without outside assistance.

Autonomous mobile robotics is a challenging research topic for several reasons. First, a mobile robot should able to identify features, detect obstacles, patterns and target, learn from experience, find a path and build maps, and navigate. These abilities of mobile robot require the simultaneous application of many research disciplines (e.g. Engineering and computer science).

Secondly, autonomous mobile robots are the closest approximation of intelligent agents. For centuries people have been interested in building machines that can think and make decisions based on the environment around them. To satisfy this goal mobile robotics research has increasingly incorporated artificial intelligence enabling the machines to mimic living beings.

Thirdly, there are many applications for mobile robots. Transportation, surveillance, inspection, cleaning and entertainment, military operations in complex hazardous environments, hostile environments such as Mars trigger even more unusual locomotion mechanisms, are just some examples. Other commercial robots operate not where humans cannot go, but rather share space with humans in human environments. These robots are compelling not for reasons of mobility but because of their autonomy, and so their ability to maintain a sense of position and to navigate without human intervention is paramount.

The design of mobile robots involves the integration of many different bodies of knowledge. To solve locomotion problems, the mobile robot must understand mechanism and kinematics, dynamics and control theory. Localization and navigation demand knowledge of computer algorithms, information theory, artificial intelligence, and probability theory. A general control scheme of autonomous mobile robot system has been illustrated in Fig.1.1.

To be sure, some form of high-level control is required to ensure that the robots do not harm any humans being or equipment or other robots. In effect, this high level of control implies an implementation of Asimov's laws (1950).

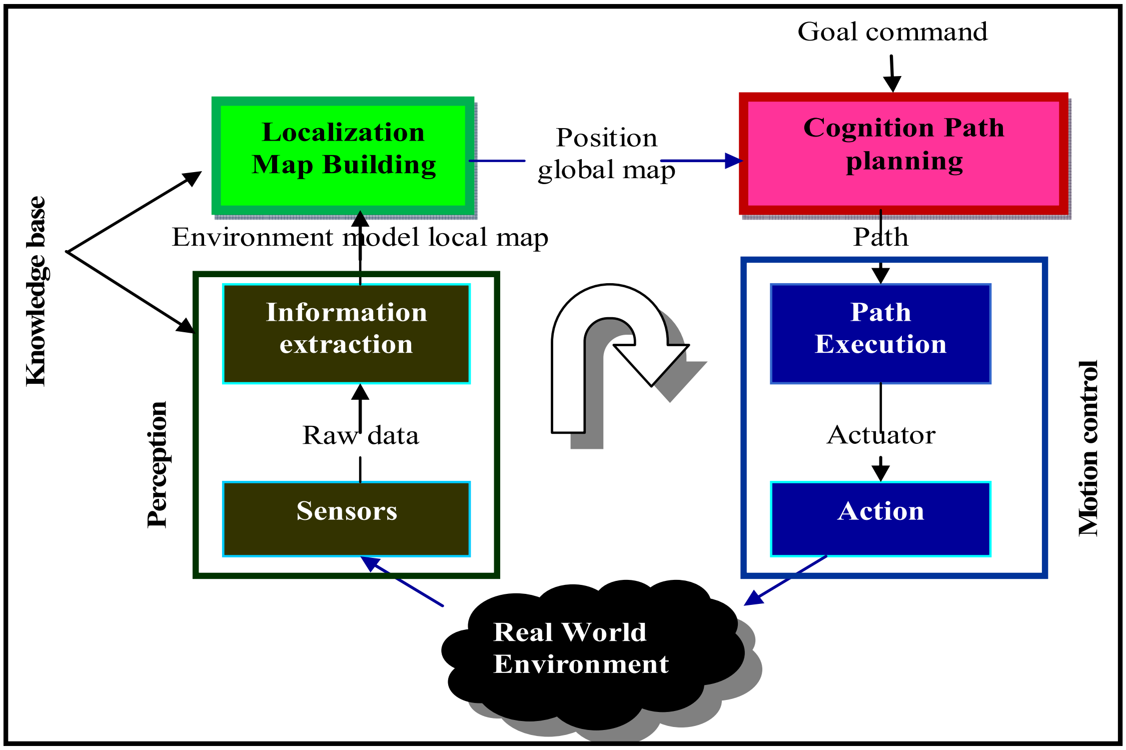


Figure 1.1. General control scheme of autonomous mobile robot system.

After introducing the original three laws, Asimov detected as early as 1950, a need to extend the first law, which protected individual humans, so that it would protect humanity as a whole. Thus, his calculating machines "have the good of humanity at heart through the overwhelming force of the First Law of Robotics. The revised set of laws is shown in the sidebar. There is a law that is greater than the First Law: "A robot may not injure humanity, or through inaction, allow humanity to come to harm".

Path analysis and planning is another exciting challenge in building autonomous mobile robots. An autonomous robot must be able to learn its environment and programming itself without assistance. It consists on finding a route from the origin of the robot to its target destination. Path analysis and planning becomes more difficult when some static as well as dynamic obstacles are added to the environment. When this occurs, it is necessary to find an alternative route. This implies a process of adaptation to the environment. In addition to avoiding collision, the other requirements are smoother motion, shorter traveling time, or more clearance from the obstacle. Therefore, the path analysis and planning involves optimization with respect to certain performance measures.

1.2 Aims and Objectives of this Research

The goal of autonomous mobile robotics is to build and control physical systems which can move purposefully and without human intervention in real-world environments which have not been specifically engineered for the robot. The development of techniques for autonomous mobile robot operation constitutes one of the major trends in the current research and practice in modern robotics. When we visit an unfamiliar place, like a new building, shopping mall or theme park, we look for guiding information to guide us to our destinations in mind. This thesis contributes towards design and development of control techniques those enables the robot to navigate in a real world environment, avoiding static and dynamic obstacles especially in crowded and unpredictably changing environment. The robot explores in the environments and identifies human understandable guiding clues to find a way to the assigned destination. The aim of this research is to idealize an existing autonomous mobile robot, on all levels. This includes the kinematics, perception, cognition, sensor fusion, path analysis, path planning and navigation. The following reactive behaviours are required to train the mobile robots to make them capable of intelligent motion. The following behaviours are required during navigation of mobile robots.

1. Obstacle avoidance behaviour, so that the mobile robot able to avoid collisions with both static obstacles and dynamic obstacles in various environments.
2. Wall following behaviour, so that mobile robot cannot trap in loop as the mobile robot detects an obstacle in the front while the target tracking control mode is on operation.
3. Target searching behaviour, so that mobile robot quickly moves towards the target if there are no obstacles around the robot.

Another objective is to determine the shortest path from the origin of the robot to its target destination. Methods for finding the shortest path, even through obstacles, have traditionally been based on one of several models, including static obstacles and moving obstacles. This thesis purposes alternative ways for determining the best route a mobile robot can follow in any environment from its origin to its target destination with the aim to reach a specified target. The objective of a kinematic controller is to follow a trajectory described by its position and velocity profiles as function of time. Many researchers have studied kinematic behaviour and provided some adequate solutions for (kinematic) motion control of a mobile robot system. Most of controllers of mobile robot are not considering the dynamics of the system.

If the robot is kinematical stable then another challenge is to design an intelligent controller which may provide a general, robust, safe and optimised path so that mobile robot navigate in real world dynamic environment. To design an intelligent controller fuzzy logic and neural network play vital role. This is due to the fact that fuzzy if-then rules are well suited for capturing the imprecise nature of human knowledge and reasoning processes. Fuzzy logic modeling is primarily based on fuzzy sets and fuzzy if-then rules proposed by Zadeh (1965) [55] which are closely related to perception and cognitive science. On the other hand the neural networks tackle the same problems with a different strategy. The neural network is equipped with a remarkable learning capability such that a desired input output mapping can be discovered through learning by examples. These two innovative modeling approaches share some common characteristics such as i) they assume parallel operations, ii) they are well known for their fault tolerance capabilities and iii) they are often called model free modeling approaches. As a result many researchers are trying to integrate these two schemes to generate hybrid models that can take advantage of the strong points of both. This is also the motivation for proposed research which aims at providing an integrate framework capable of using both neural networks and fuzzy inference systems. This thesis also proposes two integrated models Adaptive Neuro-Fuzzy Inference System (ANFIS) and Human Perception Based Heuristic Rule Base Neural Network (HRBN). These purposed approaches are appropriate for designing of intelligent controller. Petri nets model has been used to avoid inter collision among multiple robots in purposed thesis.

A ROBNAV software using C++ has been developed to demonstrate the simulation test (Appendix-A). NITR (Appendix-C.1) (developed and design in the laboratory), Khepera-II (Appendix-C.2), Khepera-III (Appendix-C.3), and Koala (Appendix-C.4) mobile robots has been used to obtained experimental results. A series of simulations and experimental results shows the effectiveness of the proposed control scheme and the robustness of the fuzzy, neural, ANFIS (Adaptive Neuro Fuzzy Inference System) and HRBN (Heuristic Rule Base Neural network) controllers. This research is devoted to the design and development of some control techniques for navigational path analysis of mobile robot in various environments.

1.3 Outline of the Research Work

The processes as outlined in this thesis are broadly divided into eight chapters. Following the introduction, Chapter 2 provides a state of the art review of navigation, kinematics analysis, fuzzy logic controller, neural controller, adaptive neuro-fuzzy controller and heuristic rule base neural controller of mobile robot.

In Chapter 3 analyses the kinematics of mobile robots. A wheeled mobile robot is considered for the kinematic analysis. It explains how a desired trajectory can be obtained using kinematic stability during navigation.

Chapter 4 defines the concept of the fuzzy logic and outlines the methodology used to design an intelligent fuzzy logic controller which enables the mobile robot to navigate successfully in real world environment.

Chapter 5 discusses the neural network technique being used for navigation of mobile robots. In Chapter 6 Navigation of mobile robots using Adaptive Network based Fuzzy Inference System (ANFIS) has been described.

In Chapter 7 Human Perception Based Navigation control of Heuristic Rule Base Neural network (HRBN) controller for mobile robot has been discussed. In Chapter 8 a detailed report of results and discussion has been given. This chapter summarises the findings of all chapters discussed before.

Finally in Chapter 9 conclusions of this research and future directions for further investigation has been discussed.

The paper published related to the chapter has been listed in the last section of the chapter.

2 Literature Review

This chapter reviews the work related to the development of navigational path analysis and planning of mobile robot in various environments. The progress made in past decades in the field of navigational path analysis of mobile robot and techniques used to design the intelligent controller has been described. This chapter presents a literature review of past and recent developments in area of kinematics analysis and artificial intelligence techniques used for navigation of mobile robots.

2.1 Introduction

A significant amount of research has been published in many aspects related to mobile robots. A literature review cannot simply be a catalog of all the articles published on a subject, the list would be much too long and could not be include each contribution. The alternative is to include in this chapter only those contributions that cover to kinematics stability of mobile robots which provides desired trajectory and artificial intelligence technique that helps to design an intelligent controller for robot. A large number of researchers have used kinematic models to develop motion control strategy for mobile robots. The ultimate goal of mobile robotics research is to endow the robots with high intellectual ability, of which navigation in an unknown environment is achieved by using on line sensory information. It summarizes the past work, mostly in computational geometry and robotics, and discusses possible directions for research.

Another challenge in literature review is that even the perception of what constitutes progress varies widely in the research community. The representations would be difficult to extend other scenarios where a robot may need to seek out optimal path and track the target in the competing clutter environment on the basis of their semantic significance. Despite these challenges, the next sections review in this article and highlights some of the more interesting, important and experimental milestones. This chapter provides details survey report within important aspects of what the researchers have worked in the area of navigational path analysis and planning for mobile robot using fuzzy logic, neural network, adaptive neuro-fuzzy and heuristic rule base neural network technique.

2.2 Navigation of Mobile Robots

The development of techniques for autonomous navigation in real-world environments constitutes one of the major trends in the current research on robotics. One of the main problems in mobile robot navigation is the determination of the robot position [1]. An important problem in autonomous navigation is the need to cope with the large amount of uncertainty that is inherent of natural environments [2]. Navigation of mobile robot is an active area of research with many potential military and civilian applications. Yet, there are many unsolved problems which probably either need a breakthrough in the current theories or a completely new approach for the solution. Extraordinary abilities of humans in doing these tasks without any measurement have inspired many researchers [3]. Navigation for mobile robots can be well-defined in mathematical (geometrical) terms. It also involves many distinct sensory inputs and computational processes. Elementary decisions like turn left, or turn right, or run or stop is made on the basis of thousands of incoming signals [3-6]. Thus it is necessary to define what navigation is and what the function of a navigation system? Navigation is traditionally defined as the process of determining and maintaining a trajectory to a goal location [5]. Biological navigation behaviours have been an important source of inspiration for robotics in the past decade. According to Levitt and Lawton [7], navigation consists of answering three questions: (a) “Where am I?” (b) “Where are other places with respect to me?” and (c) “How do I get to other places from here?” However, biological systems do not necessarily require all that knowledge to navigate, but they usually work on a “how do I reach the goal?” basis. Most systems typically deal with different degrees of knowledge depending on the circumstances. Navigation can be classified as two broad group indoor and outdoor navigations.

2.2.1 Indoor Navigation

From the pioneering robotic vehicle work by Giralt et al. [8] in 1979, and later by Moravec [9] in 1983, and Nilsson [10] in 1984, it became clear that, implicitly or explicitly, meant for navigation to incorporate within it some knowledge of what the computer was supposed to see. When sequences of images were used to represent space, the images taken during navigation were submitted to some kind of appearance-based matching between the perception and expectation. All of these and subsequent efforts fall into three broad groups.

- **Map-Based Navigation:** Map-Based Navigation is the systems that depend on user-created geometric models or topological maps of the environment. In this method information acquired from the robot's onboard sensors is compared to a map or world model of the environment [11]. If features from the sensor-based map and the world model map match, then the vehicle's absolute location can be estimated [12].
- **Map-Building-Based Navigation:** Map-Building-Based Navigation is the systems that use sensors to construct their own geometric or topological models of the environment and then use these models for navigation [13].
- **Map less Navigation:** Map less Navigation is the systems that use no explicit representation at all about the space in which navigation is to take place, but rather resort to recognizing objects found in the environment or to tracking those objects by generating motions based on visual observations [14].

2.2.2 Outdoor Navigation

Outdoor Navigation usually involves obstacle-avoidance, landmark detection, map building updating, and position estimation. Outdoor navigation can still be divided into two classes according to their level of structure of the environment.

- **Structured environment:** Structured environment first reported in the literature is by Tsugawa et al. [15] for a car that could drive autonomously. The navigation relied mostly on obstacle avoidance. In general, outdoor navigation in structured environments requires some sort of road-following. Road-following means an ability to recognise the lines that separate the lanes or separate the road from the berm, the texture of the road surface, and the adjoining surfaces etc. [16].
- **Unstructured environment:** An outdoor environment with no regular properties that could be perceived and tracked for navigation may be referred to as unstructured environment [17]. In such a situation the vision system can make use of at most a generic characterization of the possible obstacles in the environment.

Reactive-based approaches are widely used in autonomous navigation. However, in complex unknown environments, pure reactive-based navigation still poses a few challenges since it can be easily trapped by a local minimum and may produce some extra maneuvers [18]. During the last decade, the research communities in mobile robotics have paid lot of attentions, to the development of different control architectures for navigation of mobile robots. For this, mainly two principle designs have been adopted. One is called the functional or horizontal decomposition, Fig. 2.1; the other is the behavioural or vertical decomposition, Fig. 2.2. It is found that the research for navigation of mobile robot has to be modified in many terms. Robot localization with multiple sensors using interval analysis deals with the robot localization problem in a nonlinear and global way and bypasses the data association step [19]. Research may be done in finding out the optimal navigation technique for several mobile robots. Technical details may be found out to achieve various interactive perceptions (e.g. communications) between the robots and to recognise the obstacle ahead. Using the environment information obtained at each instant of time‘t’, a strategy may be adopted permitting the robot to reach the target position. At the same time, the robot should avoid the different obstacles situated in the robot work place. The intelligent control provides conflict-free shortest path, minimum time motion planning and deadlock avoidance [20].

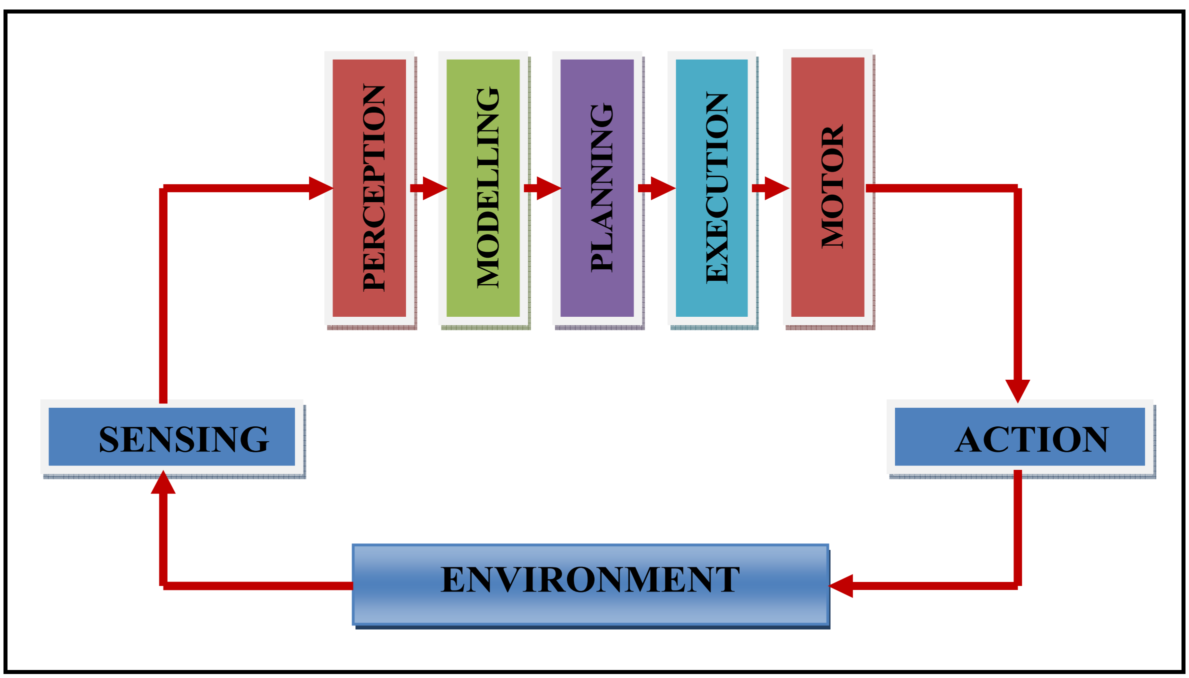


Figure 2.1.Flow diagram of the horizontal decomposition method for robot navigation.

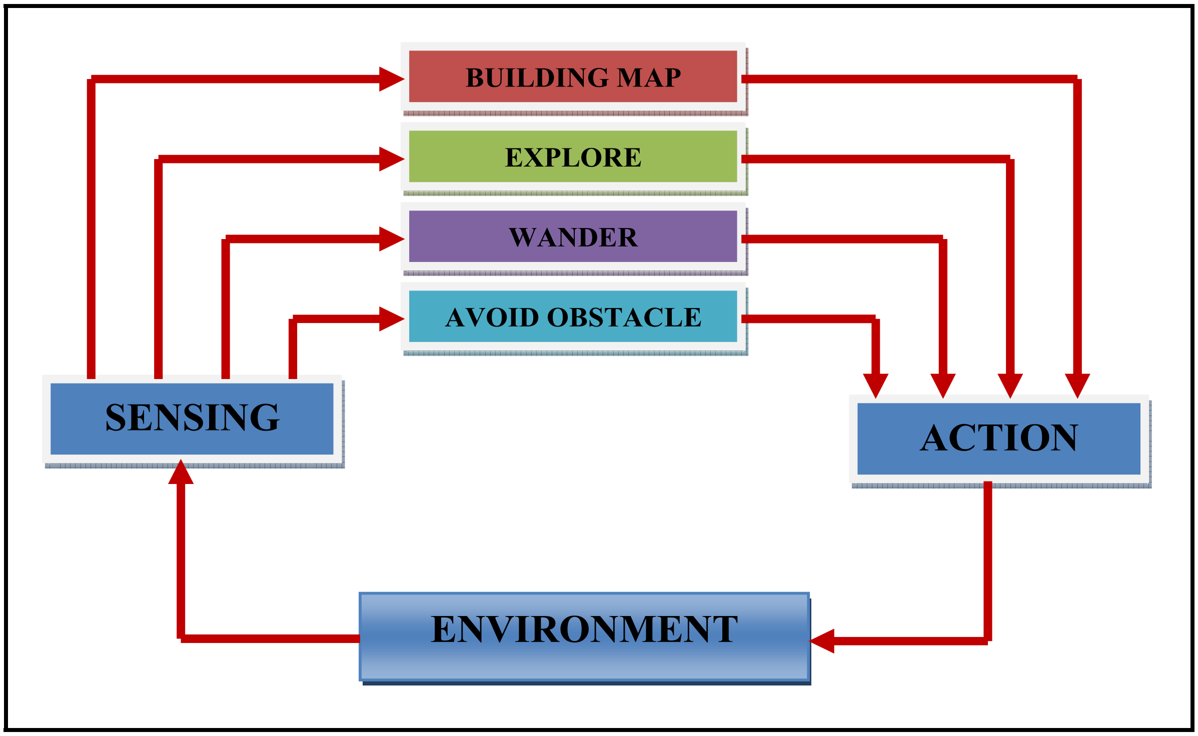


Figure 2.2.Flow diagram of the vertical decomposition method for robot navigation.

Keeping in view of the various research publications in the recent years in this field, attempt has been made to summarise the various navigation techniques for mobile robots. For reviewing the approaches for navigation of mobile robots, the investigation has been divided into five main segments. In the first part effort has been made to find out the kinematic stability of mobile robot. The next part mainly deals with various controllers being used for navigation of mobile robot. These controllers are classified into four divisions as Fuzzy Logic Controller (FLC), Neural Controller (NC), Adaptive Neuro Fuzzy Controller (ANFC) and Heuristic Rule Base Network (HRBN) controller. The next section review the published paper in the area of kinematics of mobile robot as well as techniques used in this thesis for navigation of mobile robots.

2.3 Kinematics of Mobile Robot

This section provides a detailed survey report of kinematics of mobile robot. With reference to the unicycle kinematics, this part review several control strategies for trajectory tracking and posture stabilization in an environment free of obstacles. A kinematic methodology is the first step towards achieving these goals.

Mobile robots are more energy efficient than legged or treaded robots on hard, smooth surfaces, and will potentially be the fist to find widespread application in industry, because of the hard, smooth plant floors in existing industrial environments [21]. Several mobility configurations can be found in the applications as mentioned by Jones et al. [22]. The most common for single-body robots are differential drive and synchro drive tricycle or car-like drive, and omnidirectional steering [23]. Beyond the relevance in applications, the problem of autonomous motion planning and control of mobile robot has attracted the interest of researchers in view of its theoretical challenges [24]. The motion control of wheeled mobile robots has drawn considerable attention over the past few years. The nonholonomic behaviour in robotic systems is particularly interesting, because it implies that the mechanism can be completely controlled with a reduced number of actuators. In particular, these systems are a typical example of nonholonomic mechanisms due to the perfect rolling constraints on the wheel motion [25]. Several controllers were proposed for mobile robots with nonholonomic constraints, where the two main approaches to controlling mobile robots are posture stabilization and trajectory tracking.

The aim of posture stabilization is to stabilize the robot to a reference point, while the aim of trajectory tracking is to have the robot follow a reference trajectory. For mobile robots trajectory tracking is easier to achieve than posture stabilization [26]. Path planning and motion-planning involve finding a continuous path and trajectory, respectively, from the initial position to the final position that avoids obstacles in the environment. The feedback stabilization at a given posture cannot be achieved via smooth time-invariant control [27]. This indicates that the problem is truly nonlinear; linear control is ineffective, even locally, and innovative design techniques are needed. The motion control problem of wheeled mobile robots in environments without obstacles with reference to the popular unicycle kinematics, the dynamic feedback linearization is an efficient design tool leading to a solution simultaneously valid for both trajectory tracking and set point regulation problems [28]. After a preliminary attempt at designing local controllers, the trajectory tracking problem was globally solved in by using a nonlinear feedback action [29]. A recursive technique for trajectory tracking of nonholonomic systems in chained form can also be derived from the back stepping paradigm [30]. As for posture stabilization, both discontinuous and time-varying feedback controllers can be used. Smooth time-varying stabilization was pioneered by Samson [31], while discontinuous control has been used in various forms [32] where dynamic feedback linearization has been extended to the posture stabilization problem. Dynamics of wheeled mobile robots are nonholonomic and pose is challenging problems for control design and stability analysis [33]. Under output-tracking control laws the dynamics can be formulated in terms of full-state tracking errors which offers some properties that allow better understanding of the internal and zero dynamics of the tracking-error system and more insights to the trajectory tracking stability [34]. An ideal automatic driving control system should be able to comply with changes in slip conditions so as to optimise the control performance.

Trajectory tracking is more natural for mobile robots. Usually, the reference trajectory is obtained by using a reference robot; therefore, all the kinematic constraints are implicitly considered by the reference trajectory [35]. A generic kinematic control, which is directly applicable to any type of wheeled mobile robot, proposed by Gracia et al. [36]. The neural kinematic controller is applied to compensate the uncertainties in the kinematic parameters of the mobile robot. To analyze the stability of a general class of mobile robot path-tracking algorithms taking into account explicitly the computation and communication delays in the control loop. The delay problem can be solve directly the transcendental characteristic equation that appears when the time delay is considered. This is applicable for straight paths and paths of constant curvature [37]. The global stability of the neural network is guaranteed by qualitative analysis and the Lyapunov stability theory [38]. Fierro and Lewis [24] developed an artificial neural network-based controller by combining the feedback velocity control technique and torque controller, using a multilayer feed forward neural network. But the controller structure and the neural network-learning algorithm are very complicated and it is computationally expensive [39]. The control approach for the mobile robot has the properties to quickly drive the position error to zero and to indicate better smooth movement in the tracking control process. These features are due to continuous online learning and adaptive capability of analog neural networks [40]. The dynamic wave expansion neural network for path generation in a dynamic environment for mobile robots is parameter-free, computationally efficient, and its complexity does not explicitly depend on the dimensionality of the configuration space [41].

The autonomous navigation wheeled robots requires integrated kinematic and dynamic control to perform trajectory tracking, path following and stabilization. The coupling effect between linear and angular motion dynamics is considered in the fuzzy steering by building appropriate linguistic rules [42]. A fuzzy logic approach can be used in order to minimise the position and orientation errors caused by odometric problems. The fuzzy logic maps the inputs heading and distance errors determined by the odometry readings to the outputs of translational and rotational speed of the mobile robot [43]. Fuzzy inference mechanism extended that compensation for environmental perturbations as variable friction. A fuzzy-neural control algorithm realizes the obstacle avoidance of the mobile robot. Using the self location function, the mobile robot could locate itself in a world coordinate system [44]. This indicates that the problem is truly nonlinear; linear control is ineffective, even locally, and innovative design techniques are needed. The existing approaches of sensor-based motion planning tend to deal solely with kinematic and geometric issues, and ignore the system dynamics. Any nonlinear optimal control requires a solution to a two-point-boundary-value problem that is salvable only by numerical iteration. Consequently, an improved control can he obtained by modifying the suboptimal control in such a way that the distance aforementioned is minimised as much as possible in closed form [45]. The sensor with classical rangefinders allows the use of practically unmodified Monte Carlo algorithms, with the additional advantage of being able to easily detect occlusions caused by moving obstacles [46]. An iterative learning rule with both predictive and current learning terms is used to overcome uncertainties and the disturbances in the system [47].

The problem of terrain acquisition presents a special case of robot motion planning. The harmonic drive system for non-linear controller to compensate for kinematic error in the presence of flexibility in high-speed regulation and trajectory tracking application has been proposed by Gandhi et al. [48]. In it, a robot that operates in an unfamiliar scene populated with a finite number of objects of unknown shapes and dimensions is asked to cover the scene and build its complete map using some sort of sensory feedback and generating as short a path during operation as possible [49]. The behaviour of space robots with torque and attitude controller has been discussed by Pathak et al. [50]. A dynamical local path-planning algorithm of an autonomous mobile robot available for moving obstacle avoidance as well as stationary obstacle avoidance using artificial pressure and nonlinear friction [51]. A receding horizon controller is may used for tracking control of wheeled mobile robots subject to nonholonomic constraint in the environments without obstacles. The control policy is derived from the optimization of a quadratic cost function, which penalizes the tracking error and control variables in each sampling time [52]. This methods, improve the domain of applicability of a wide range of obstacle avoidance methods [53]. Basically, both trajectory tracking and posture stabilization controllers can be implemented with on-board computing power.

2.4 Fuzzy Logic Controller for Mobile Robot

Fuzzy Logic technique plays an important role to design the intelligent controller for mobile robot. This technique can be used for navigation of mobile robots. Fuzzy set theory provides a mathematical framework for representing and treating uncertainty in the sense of vagueness, imprecision, lack of information and partial truth. Fuzzy control systems employ a mode of approximate reasoning that resembles the decision-making process of humans. A fuzzy system is usually designed by interviewing an expert and formulating the implicit knowledge of the underlying process into a set of linguistic variables and fuzzy rules. In particular for complex control tasks, obtaining the fuzzy knowledge base from an expert is often based on a tedious and unreliable trial and error approach [54]. Fuzzy set theory was introduced by Lofti Zadeh in the mid sixties. In 1965 Lotfi Zadeh proposed fuzzy set theory, and published a paper [55]. Fuzzy logic has been applied to diverse fields, from control theory to artificial intelligence. This section presents a variety of fuzzy logic techniques which address the challenges posed by autonomous robot navigation.

Autonomous mobile robot navigation in uncertain and dynamic environments demands adaptation and perception capabilities. Reactive control strategies imply a strong dependency on sensed information about the robot's environment. Thus, imprecision and uncertainties in perception from sensors have to be considered [56]. While the rules are based on qualitative knowledge, the membership functions defining the linguistic terms provide a smooth interface to the numerical process variables and the set-points [57]. Stability analysis of fuzzy systems is a very important research field in fuzzy systems practically from the pioneer work of E.H. Mamdani on fuzzy control applications [58]. A Mamdani controller is usually used as a feedback controller. Since the rule base represents a static mapping between the antecedent and the consequent variables, external dynamic filters must be used to obtain the desired dynamic behaviour of the controller [59]. The control protocol is stored in the form of if-then rules in a rule base which is a part of the knowledge base. While the rules are based on qualitative knowledge, the membership functions defining the linguistic terms provide a smooth interface to the numerical process variables and the set-points [60]. Intelligent control plays an important role when employing mobile robots in unstructured, unknown, and dynamic environments. The task complexity of intelligent control is greatly reduced by dividing the overall task into subtasks. These subtasks are modeled as perception-action units, called behaviours. The reduced task complexity in a behaviour-based approach increases responsiveness to environmental dynamics [61]. Systems equipped with fuzzy logic controllers give rise to nonlinear dynamic systems. This theory provides an overall perspective on the behaviour modes of the system, which can be used as a guide for the search of concrete behaviours [62]. Fuzzy systems belong to the family of nonlinear systems and they can have, in general, a complex analytical description [63]. It is not easy and time consuming for human experts to examine all the input-output data from a mobile robot to find a number of proper rules for a fuzzy controller. To copy with this difficulty, an intelligent mobile robot with automatic fuzzy controller design approaches is necessary [64]. It should also be noticed that although the operating range of the input is restricted by the saturation, the range of the other system variables cannot be bounded. This is in fact the cause of the troubles with the nonlinear nature of the saturation [65]. In this context, fuzzy logic is often adopted to overcome the difficulties of modeling the unstructured, dynamically changing environment, which is difficult to express using mathematical equation [66]. A class of fuzzy control laws can be formulated using the Lyapunov's direct method, which can guarantee the convergence of the steering errors [67]. The fuzzy controller can be optimised by using the schema co-evolutionary algorithm, which finds an optimal solution [68]. The main problem in fuzzy control involves the design of the fuzzy knowledge base. Various approaches to this problem have been proposed, including trial and error. For a mobile robot to intermesh navigation in various environments using fuzzy logic controller shown in Fig.2.3 represents significant progress for the entire research community. In Fig.2.3,

Left-obs = Left obstacle distance, Right-obs = Right obstacle distance, Front-obs = Front obstacle distance, Tar-ang= Target angle, Left-v = velocity of left wheel, Right-v = velocity of right wheel and Med= Medium.

The fuzzy rules are if-then rule as: If (Antecedent) Then (consequent).

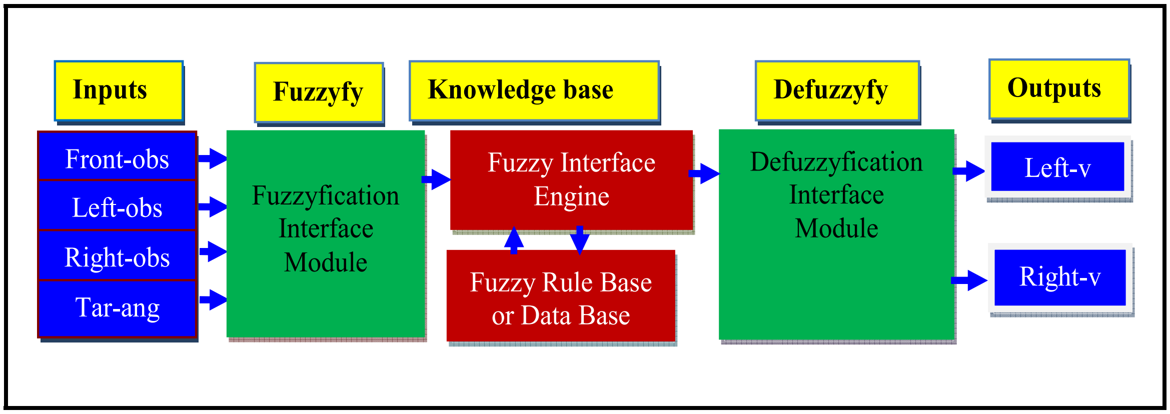


Figure 2.3. Schematic diagram of the fuzzy logic controller for mobile robot.

An adaptive-resonance theory based fuzzy controller, including an adaptive-resonance theory based environment recogniser, a comparer, combined rule bases, and a fuzzy inferring mechanism, is introduced for the purpose of the adaptive navigation of the quadruped robot [69]. The adaptive fuzzy logic control based on physical properties of wheeled inverted pendulums makes use of a fuzzy logic engine and a systematic online adaptation mechanism to approximate the unknown dynamics [70]. Fuzzy adaptive extended information filtering is to improve estimation accuracy and robustness for the localization system, while the system lacks sufficient information of complete models or the process and measurement noise varies with time [71]. The unmanned control of the steering wheel is, at present, one of the most important challenges facing researchers in autonomous vehicles within the field of intelligent transportation systems [72]. Once this control architecture has been implemented, installed, and tuned, the resulting steering maneuvering is very similar to human driving, and the trajectory errors from the reference route are reduced to a minimum. In the controller a rule base of positive rules can be specified by an expert for directing the vehicle to the target in the absence of obstacles, while a rule base of negative rules can be experimentally determined from expert operation of the vehicle in the presence of obstacles [73].

Fuzzy logic system promises an efficient way for obstacle avoidance. However, it is difficult to maintain the correctness, consistency, and completeness of a fuzzy rule base constructed and tuned by a human expert. Reinforcement learning method is capable of learning the fuzzy rules automatically [74]. Martinez et al. [75] have considered a problem which is consisted of achieving sensor based motion control of mobile robot among obstacles in structured and unstructured environments with collision-free motion. Sensor-based navigation method, which utilised fuzzy logic and reinforcement learning for navigation of mobile robot in uncertain environments, has been proposed by Boem et al. [76] they have discussed about the navigation of mobile robot using fuzzy logic.

The concepts of car maneuvers, fuzzy logic control, and sensor-based behaviours are merged to implement the human-like driving skills by an autonomous car-like mobile robot. Four kinds of Fuzzy logic controller, fuzzy wall-following control, fuzzy corner control, fuzzy garage-parking control, and fuzzy parallel-parking control, are synthesized to accomplish the autonomous fuzzy behaviour control [77]. The architecture for the fuzzy controller is a hierarchical scheme which combines seven modules working in series and in parallel [78]. The scaling factors and the coefficients of the sliding surface for the control of the steering angle and forward–backward velocity of a car-like mobile robot are adopted by that for the control of two motors [79]. Wang [80] has used fuzzy systems to model higher levels of hierarchical systems and design controllers for the hierarchical systems. Seraji's [81] paper presents a new strategy for behaviour- based navigation of field mobile robots on challenging terrain. Outdoor environments are particularly challenging for mobile robots as they offer dynamic, unstructured, and highly variable situations where the inconsistency of the terrain, the irregularity of the product, and the open nature of the working environment result in complex problems of identification, modeling, sensing, and control [82].

One important problem in autonomous robot navigation is the effective following of an unknown path traced in the environment in compliance with the kinematic limits of the vehicle, i.e., bounded linear and angular velocities and accelerations. In this case, the motion planning must be implemented in real time and must be robust with respect to the geometric characteristics of the unknown path, namely curvature and sharpness [83]. The stabilizing controller is designed as a state optimal controller and second application is the optimization method applied to the design of a fuzzy controller for vision-based mobile robot navigation [84]. The fuzzy error correction control system can be used to navigate a robot along an easily modifiable path in a well-structured environment. The fuzzy engine gives outputs commands for the robot wheels. These commands determine the necessary angle of rotation to correct the direction of travel in order for the robot to remain on the path [85]. Das et al. [86] have assumed a control structure that makes possible the integration of a kinematic controller and an adaptive fuzzy controller for trajectory tracking for nonholonomic mobile robots. The hybrid controller is able to choose a better position according to the circumstances encountered [87]. The information about the global goal and the long-range sensory data are used by the first layer of the planner to produce an intermediate goal, referred to as the way-point that gives a favorable direction in terms of seeking the goal within the detected area. The second layer of the planner takes this way-point as a sub goal and, using short-range sensory data, guides the robot to reach the sub goal while avoiding collisions [88]. Designing the controller on account of nonholonomic constraints gain more accurate position and velocity control, a self-organized fuzzy controller can be used to find solutions of optimal fuzzy input and output membership functions [89] and to determine a rule base process.

The fuzzy multi sensor data fusion scheme provides a novel mechanism to efficiently integrate task scheduling, action planning and motion control in a unified framework. The theoretical development of a complete navigation problem of an autonomous mobile robot is the situation for which the vehicle tries to reach the endpoint is treated using a fuzzy logic controller [90]. An efficient design methodology that allows starting with any kind of fuzzy controller and subsequently transforming it until a system suitable for easy digital signal processing implementation is obtained [91]. Navigation based on processing some analog features of Radio Frequency Identification signal is a promising alternative to different types of navigation methods in the state of the art. The main idea is to exploit the ability of a mobile robot to navigate a priori unknown environments without a vision system and without building an approximate map of the robot workspace, as is the case in most other navigation algorithms [92]. In the soccer game strategy Radio Frequency data transmitter is used to communicate among robot [93]. The development of the controllers is carried out by means of a reconfigurable platform based on field-programmable gate arrays. This platform combines specific hardware to implement fuzzy inference modules with a general-purpose processor, thus allowing the realization of hybrid hardware/software solutions [94]. The merger method is applied to fuzzy rule base simplification by automatically replacing the fuzzy sets corresponding to a given cluster with that pertaining to cluster prototype [95]. Target tracking requires team coordination to maintain a desired formation and to keep team-mates and target together. Generally, distributed autonomous systems using multiple robots are considered superior to others in terms of reliability, expandability, and flexibility. In contrast to a single robot system; they provide increased robustness by taking advantage of inherent parallelism and redundancy. Moreover, the versatility of a multi-robot system can provide the heterogeneity of structures and functions required to undertake different missions in unknown environmental conditions [96]. Research in autonomous multi-robot systems often focuses on mechanisms to enhance the efficiency of the group through some form of cooperation among the individual agents. One of the greatest challenges in robotics is to create machines that are able to interact with unpredictable environments in real time [97]. Intriguingly, a similar relationship between group size and efficiency has been documented in social robots.

2.5 Neural Controller for Mobile Robot

The human brain is very complex, nonlinear and parallel computer. There are billions of neurons and trillions of connections between them. The interest in neural network stems from the wish of understanding principles leading in some manner to the comprehension of the basic human brain functions, and to building the machines that are able to perform complex tasks. Neural network theory revolves around the idea that certain key properties of biological neurons can be extracted and applied to simulations, thus creating a simulated brain. There is a significant interest in autonomous mobile robots which may be defined as vehicles that are capable of intelligent autonomous navigation.

Robots must be able to understand the structure of the environment [98]. To reach their targets without collisions, the robots must be endowed with perception, data processing, recognition, learning, reasoning, interpreting, and decision-making and action capacities. A first wave of interest in neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943 [99]. In 1949 Hebb [100] formed the basis of ‘Hebbian learning’ which is now regarded as an important part of neural networks theory [101]. About this time of neural network development, the digital computer became more widely available and its availability proved to be of great practical value in the further investigation of neural networks performance. Rosenblatt [102] constructed neuron models in hardware during 1957. These models ultimately resulted in the concept of the Perceptron. This was an important development and the underlying concept is still in wide use today. Widrow and Hoff [103] were responsible for simplified artificial neuron development. When Minsky and Papert published their book Perceptrons in 1969 [104] in which they showed the deficiencies of perceptron models, most neural network funding was redirected and researchers left the field.

If human understand how an animal controls its behaviour, and comparable technology is available, it should be possible to build a robot that behaves the same way. Recent advances in both knowledge and technology have begun to make this possibility a realistic aim in invertebrate neuroscience [105-107]. Neural circuit are capable of producing coordinated patterns of high-dimensional rhythmic output signals while receiving only simple, low-dimensional, input signals [105]. There are now a growing number of studies in which hypotheses for the behavioural function of neural circuits are tested by implementing them as controllers for robots and evaluating the robot behaviour [108]. An artificial neural network is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks [109]. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation [110]. They can be used to model complex relationships between inputs and outputs or to find patterns in data [111]. However, generally, the evolved neural controllers could be fragile in inexperienced environments, especially in real worlds, because the evolutionary optimization processes would be executed in idealized simulators. This is known as the gap problem between the simulated and real worlds. To overcome this, Kondo [112] has focused on an evolving on-line learning ability instead of weight parameters in a simulated environment. Basically, the control of a robot arm and the control of a mobile robot is similar the controller [113]. First plans a path, the path is transformed from Cartesian domain to the joint or wheel domain using the inverse kinematics of the system and finally a dynamic controller takes care of the mapping from set points in this domain to actuator signals. However, in practice the problems with mobile robots occur more with path-planning and navigation than with the dynamics of the system. Recently, a new paradigm of cognitive science has been emerged [114]. The hallmark of this new approach is the focus on the situated and embodied nature of intelligence. Research in so-called behaviour-based artificial intelligence [115], embodied neurobiology, and embodied cognitive science [116] has challenged the traditional view according to which intelligence is an abstract, symbolic process independent of physical implementation. The artificial life approach to evolutionary robotics is used as a fundamental framework for the development of a modular neural control of autonomous mobile robots

[117]. The applied evolutionary technique is especially designed to grow different neural structures with complex dynamical properties. This is due to a modular neuro dynamics approach to cognitive systems, stating that cognitive processes are the result of interacting dynamical neuro-modules [118]. Relevant brain centers, known as Mushroom Bodies and Central Complex were recently identified in insects: though their functional details are not yet fully understood, it is known that they provide secondary pathways allowing the emergence of cognitive behaviours [119]. In recent years, mobile robots have been required to become more and more autonomous in such a way that they are able to sense and recognise the three-dimensional space in which they live or work [120]. Werbos et al. [106] have reviewed the empirical results which fit the theory, and suggested important new directions for research, within the scope of NSF's recent initiative on cognitive optimization and prediction.

The purpose of the learning rule is to train the network to perform some task. There are many types of neural network learning rules [121]. They fall into three broad categories: supervised learning, unsupervised learning and reinforcement learning. The mobile robot navigation deals with application of back propagation algorithm in both, supervised and reinforcement learning approaches [122]. A hybrid approach for the autonomous motion control of robots in cluttered environments with unknown obstacles is introduced by Maravall et al. [123]. Decision making system is the most important part of the robot soccer system [124]. As the environment is dynamic and complex, one of the reinforcement learning methods is employed in learning the decision-making strategy. Nelson et al. [125] have described the evolutionary training of artificial neural network controllers for competitive team a game playing behaviours by teams of real mobile robots. A neural network based machine vision system, which is intended to act as a reconfigurable inspection tool, for use in manufacturing environments [126, 127]. Discriminative training is accomplished in a supervised manner, using gradient-descent method. The approach is suitable for navigation and for map learning [128]. Many current machine learning paradigms has been used for this purpose, however, result in opaque models that are difficult, if not impossible to analyze, which is an impediment in safety-critical applications or application scenarios where humans and robots occupy the same workspace [129]. The hybrid architecture using band pass filtering, cross-correlation and recurrent neural networks can be used to develop a robust, accurate and fast sound-source localisation model for a mobile robot [130]. The new approach in robotic learning systems has been proposed by Burgsteiner et al. [131]. It provides a method to use a real-world device that operates in real time, controlled through a simulated recurrent spiking neural network for robotic experiments. Robot path-planning techniques can be divided into two categories. The first, called local planning relies on information available from the current 'viewpoint' of the robot. This planning is important, since it is able to deal with fast changes in the environment. The second situation is called global path-planning, in which case the system uses global knowledge from a topographic map previously stored into memory. Although global planning permits optimal paths to be generated [132], it has its weakness. Spiking neural networks [133], as the third generation of artificial neural networks, have unique advantages and are good candidates for robot controllers. In the controller the integrated-and firing model can be used and the Spiking neural network is trained by the Hebbian learning algorithm [134]. The transportation using wheels is one of the most popular transportation mechanisms for mobile robots because of its high energy efficiency, simple mechanisms and well-investigated control systems [135]. Wheel type mobile systems are the most popular transportation mechanisms because the energy efficiency is high, the mechanism is simple and the control system is well investigated [136]. On the other hand, the wheel type mobile robots have difficulties in rough terrain movement. Perception and behaviour are usually considered to be separate processes. Behavioural learning, however, forms associations between perception and action, organized by reinforcement, without regard for the construction of perception [137]. The behaviour is organized as a dynamic hierarchy of independent schemas [138]. An incremental evolution method for neural networks based on cellular automata and a method of combining several evolved modules by a rule-based approach [139].

The problems of trajectory following and posture stabilization of the mobile robot with nonholonomic constraints can be solve with the recurrent neural network with one hidden layer which is trained on-line by back propagation optimization algorithm with an adaptive learning rate[140]. A direct modified Elman neural networks based decentralized controller is proposed by Chen et al. [141] to control the magnet. The dynamic model with model uncertainties and the kinematic model represented by polar coordinates are considered to design a robust control system [142]. A dynamic collision-free trajectory generation in a non-stationary environment is studied using biologically inspired neural network approaches [143].

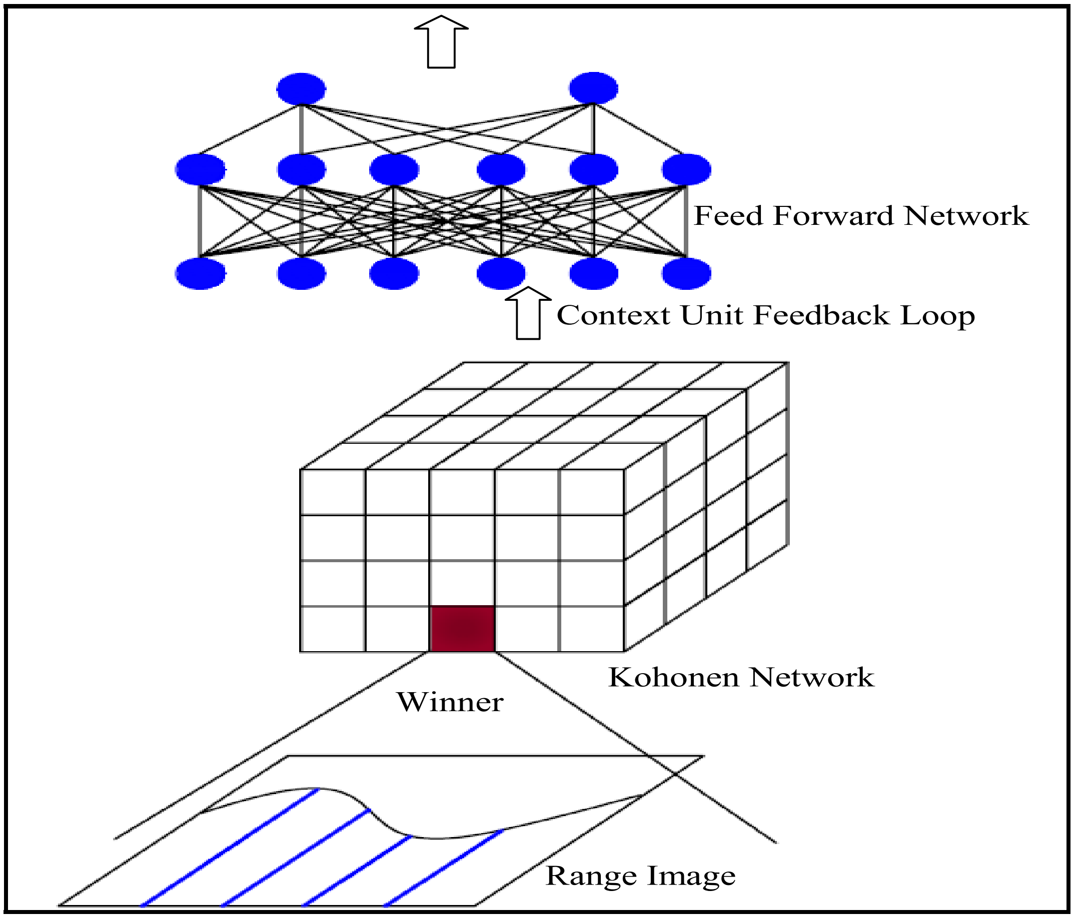


Figure 2.4. Schematic view of the neural networks used for the navigation of mobile robots, the output of the Kohonen network is fed into the feed forward network as a regression.

Hierarchical approach to solving sensor planning for the global localization of a mobile robot consists of two subsystems: a lower layer and a higher layer [144]. The lower layer uses a particle filter to evaluate the posterior probability of the localization. The higher layer uses a Bayesian network for probabilistic inference. Tani et al. [145] have presented a novel scheme for sensory-based navigation of a mobile robot. They have shown that their scheme constructs a correct mapping from sensory inputs sequences to the maneuvering outputs through neural adaptation, such that a hypothetical vector field that achieves the goal can be generated (Fig. 2.4). In general, the main focus of the research on robot mapping has been on representing the geometry of the environment with high accuracy [146]. Janet et al. [147] have discussed about the neural network technique for navigation of mobile robot. They have used Kohonen and region-feature neural networks for this purpose.

2.6 Adaptive Neuro-Fuzzy Controller for Mobile Robot

In the field of artificial intelligence, Neuro-Fuzzy refers to combinations of artificial neural networks and fuzzy logic. Fuzzy systems have the ability to make use of knowledge expressed in the form of linguistic rules, thus they offer the possibility of implementing expert human knowledge and experience. Usually, tuning parameters of membership functions is a time consuming task. Neural network learning techniques can automate this process, significantly reducing development time, and resulting in better performance. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks.

Traditional robot control methods rely upon strong mathematical modeling, analysis, and synthesis. However, operations in unstructured environments, such as in remote planets and hazardous waste sites, require robots to perform more complex tasks without an adequate analytical model [148]. Fuzzy systems and neural-networks are widely used techniques in intelligent systems [149, 150]. A fuzzy logic system has been designed with three behaviours, target seeking, obstacle avoidance and wall following [151]. The main drawback of fuzzy controller is the lack of a systematic methodology for their design. Usually, tuning parameters of membership functions is a time consuming task [152]. On the other hand neural network modeling is based on artificial neural networks which are motivated by biological neural systems and learning techniques can automate this process, significantly reducing development time, and resulting in better performance. Neural-networks are adaptive systems that can be trained and tuned from a set of samples. Once they are trained, neural-networks can deal with new input data by generalizing the acquired knowledge [153]. A learning algorithm based on neural network techniques is developed to tune the parameters of membership functions, which smoothes the trajectory generated by the fuzzy logic system [154]. Neural network modeling does not rely on human expertise. Instead, it employs a learning procedure and a given training data set to evolve a set of parameters such that the required functional behaviour is achieved. Nevertheless, it is very difficult to extract and understand that knowledge [153]. However, neural network has some disadvantages such as the local minimum points, the slow astringency, and fuzzy systems have a drawback when applied to different applications.

Moreover, the rules are often very difficult or even impossible to be determined [149]. It should be emphasized that the weights in a neural network with hard limiter as its activation function do have physical meanings the weights of a given node represent the coefficients of the hyper-plane [150]. That partitions the input space into two regions with different output values.

Mobile robot local path planning in an unknown and dynamic environment with uncertainties is one of the most challenging problems in robotics [155]. For real time autonomous navigation, the robot should be capable of sensing its environment, interpreting the sensed information to obtain the knowledge of its position and the environment, planning a real-time route from an initial position to a target with obstacle avoidance, and controlling the robot direction and velocity to reach the target [155]. The hybridisation of neural and fuzzy techniques generates neuro- fuzzy architecture and that provides human like reasoning. In this connection Ng et al. [156] have proposed a neural integrated fuzzy controller, which integrates the fuzzy logic representation of human knowledge with the learning capability of neural networks, to save nonlinear dynamic control problems. The problem of autonomous navigation applied to mobile robots has well defined as a search process within a navigation environment containing obstacles and targets by Crestani et al. [157]. Rutkowski et al. [158] have derived flexible neuro-fuzzy inference Mamdani-type systems and they have stated that it is more suitable for approximation problems. A fuzzy logic controller has been used to control the robot and has been improved by using three different neuro-fuzzy approaches by Hui et al. [159]. Fifth-order polynomial reference paths for three different size parking dimensions can be used to generate the training data to solve car-like mobile robot parking [160]. The autonomous mobile robot uses infrared and contact sensors for detecting targets and avoiding collisions. Truck backer-upper problem is a typical benchmark for many control methods in nonlinear system identification [161]. The control system is organized in a top-bottom hierarchy of various tasks and behaviours. Rusu et al. [162] have discussed a neuro-fuzzy controller for sensor-based mobile robot navigation in indoor environments. A neuro-fuzzy system architecture for behaviour-based control of mobile robot in unknown environments has been presented by Li et al. [163]. They acquired the range information by ultrasonic sensors. Garbi et al. [164] have focused the detailed of an adaptive neuro-fuzzy inference system implemented in structure of multi valued behaviours system for robotic vehicle navigation.

Adaptive Network based Fuzzy Inference System (ANFIS) is appropriate for nonlinear modeling time series prediction and intelligent control. Under the control of ANFIS approach, the mobile robots are able to avoid static and dynamic obstacles, and reach the target successfully in various environments [165]. The evolvement of soft-computing paradigms have provided a powerful tool to deal with mobile robot navigation process, which exhibits incomplete and uncertain knowledge due to the inaccuracy and imprecision inherent from the sensory system [166]. The systematic approach of soft computing techniques provides an optimal design solution based on customized optimization criteria [167]. The artificial neural network can be used as a universal learning paradigm for any smooth parameterized models, including fuzzy inference system [150]. Direct adaptive control scheme for stable path tracking of mobile robots using TSK-type recurrent neuro fuzzy system is developed by Lee et al. [168]. This study is addressed to improve the quality of the signal of the Adaptive-Network based Fuzzy Inference System [169] reducing the level of fluctuations in the output due to periodical disturbances.

Within the last decade, there has been an interest among the scientists and researchers to coordinate multiple mobile robots. This interest has stemmed both from practical considerations such as multiple robots are able to handle tasks that individual machine cannot do, for instance carrying large, bulky and heavy loads and desire to create artificial systems that mimic nature in particular by exhibiting some of the primary behaviours observed in human societies [170]. Pham et al. [171] have focused on the development of intelligent multi-agent robot teams that are capable of acting autonomously and of collaborating in a dynamic environment to achieve team objectives. An assessment of different estimation and prediction techniques applied to the tracking of multiple robots is proposed by Torres-Torriti et al. [172]. Cooperative control of multiple robots has received considerable attention in the last decade due to a wide array of applications such as moving a large number of objects, environmental monitoring, rescue missions, distributed transportation, and multipoint surveillance; such tasks cannot be efficiently accomplished by a single robot [173]. In many applications, a group of robots is required to follow a predefined trajectory while maintaining a desired spatial pattern, which is the focus of this work. In 1990, high-MIQ consumer products employing fuzzy logic began to grow in number and visibility. Somewhat later neural network techniques combined with fuzzy logic begins to be employed in a wide variety of consumer product with the capability to adopted and learn from experience [174]. Such neuro-fuzzy products are likely to become ubiquitous in the years ahead. The same is likely to happen in the realm of robotics. Industrial systems, process control and speed control of a switched reluctance motor [175]. The design and implementation of a neural fuzzy controller suitable for real-time control of an autonomous mobile robot using Generalized Dynamic Fuzzy Neural Networks learning algorithm is well presented by Er et al. [176]. According to modular robot concept, the integrated structure is constructed and its dynamic modeling is performed by Yangmin et al. [177]. Control and sensor information between the robots and the control system is supplied through radio communication [178]. The adaptive neuro-fuzzy hybrid force/motion controller is presented by Zhijun et al. [179]. The dynamic analyses of flexible robotic manipulators have been reported by Pieper [180] and Diwedi et al. [181]. The redundancy of a mobile modular manipulator is investigated to avoid tipping over of the entire robot [182]. The problem of minimum-time trajectory planning for a three degrees-of-freedom planar manipulator can be solved using a hierarchical hybrid neuro-fuzzy system.

2.7 Heuristic Rule Base Neural Controller for Mobile Robot

This section introduces a control system for a mobile robot which provides heuristic learning concretely. These learning methods are applied to design goal oriented driving behaviours and static as well as dynamic obstacle avoidance and to optimise path as well as time within the environment. The method is simple and fast in execution using the perception based heuristic rule concept. The algorithm computes the paths for the individual robots in the configuration-time space. Thereby it trades off the distance to static objects as well as with other robots and the length of the path to be traveled. Useful heuristic rules are hybridized with the artificial neural network to build the desired mapping between perception and motion.

When people make guidance on the route for the newcomers, one tells where the destinations are and then tells which path follows from the landmarks to their destination [183]. The navigation problem involves how to reach a goal avoiding obstacles in dynamic environments. These mechanisms allow the learning of both reactions and sequences of actions. This learning process involves two main tasks: first, discrimination between rules and, second, the discovery of new rules to obtain a successful operation in dynamic environments [184]. The reactive rule base governing the robot behaviour is synthesized corresponding to the various situations defined by the instant robot motion, environment and target information. Sensed ranging and relative target position signals are input to the fuzzy controller while the steering angle and the velocity change are inferred to drive the mobile robot [185]. A local navigation algorithm for mobile robots combines rule-based and neural network approaches togather. The global path environment has been classified into a number of basic local path environments to which each module has been optimised with higher resolution and better generalization [186]. Navigation algorithms have been investigated by many researchers [187]. Their methods are generally good for local navigation but may not be optimal in a global sense. To navigate in an unknown or unstructured environment, it is more desirable for the mobile robot to take intelligent decision based on its sensory information [188]. In order to adapt the robot's behaviour to any complex, and dynamic environment without further human intervention, it should be able to extract information from the environment heuristically, to perceive, and act within the environment [189]. As a result, designing of intelligent controller of a mobile robot plays an important role in robotics [190-192]. Existing approaches plan an initial path based on known information about the environment, then modify the plan locally as the robot travels or reschedule the entire path as the robot discovers obstacles with its sensors, sacrificing optimality or computational efficiency, respectively [191]. Reactive obstacle avoidance is one of the most desirable characteristics of an autonomous mobile robot. It is important for the robot to respond promptly to its surroundings, for instance, to avoid unexpected obstacles and continue traveling toward the target [192]. Autonomous wheeled mobile robot needs implementing velocity and path tracking control subject to complex dynamical constraints. Conventionally, the control design is obtained by analysis and synthesis or by domain expert to build control rules. An adaptive critic motion control design, which enables wheeled mobile robot to autonomously generate the control ability by learning through trials, is proposed by Lin et al. [193]. This searches for the most probable map such that the associated pose provides the robot with the best localization information. The problem of determining a feedback control law, robust with respect to localization errors, allowing a mobile robot to follow a prescribed path [194]. Knowledge of this attractive domain allows us to compute easily a security margin to guarantee obstacle avoidance during the path following process.

Real-time heuristic search methods interleave planning and plan executions and plan only in the part of the domain around the current state of the agents. Approaches based on the classical paradigms are not completely suitable for unpredictable and dynamic environments [184]. One general principle that can reduce the planning time in nondeterministic domains is interleaving planning and plan executions. Without interleaving planning and plan executions, the agents have to find a large conditional plan that solves the planning task [195]. The mobile robot is assumed to move in a two-dimensional workspace with continuous input from the surrounding environment. The input is a signal that reflects the distance and position of an obstacle momentarily. The neural network uses an original approach of hybrid instantaneous reinforcement learning in addition to a long-term back propagation through time learning. The second stage is to test the learned neural network with different obstacles than the ones used in learning [196]. The approach is based on qualitative representations of variations in sensor behaviour between adjacent regions in space. These representations are used to localize and guide planning and reaction [197]. During execution, the robot controller integrates this map into a reaction module.

In animals, there is evidence that the stronger their motivation for a task, the more they tend to accept as relevant those stimuli to which they previously paid no attention. It is shown how motivations and their reactivity threshold bring about perceptual generalizations that might help animals to recognise more opportunities to act [198]. This process is likely to be useful in uncertain environments, such as the real world. Designers interested in autonomous mobile robots construct machines with flexible goal achievements [92]. In particular, these robots are provided with specific motivational states that determine when to carry out a given task. In addition, the goal-objects may vary in optimality; not all are always equally attractive in relation to the same task. Multi-robot motion planning that is based on the concept of planning within dynamic robot networks [199]. The system enables multiple mobile robots that have limited ranges of sensing and communication to maneuver safely in dynamic, unstructured environments [200]. The Kino dynamic randomized motion planning techniques has been used to construct trajectories in real-time and has been discussed by Bennewitz et al. [201]. The Radio Frequency Identification technology algorithm is capable of reaching a target point in its a priori unknown workspace without vision system, as well as tracking a desired trajectory with a high precision [202]. The general aim of automation is to avoid human interventions to control and to supervise tasks. Ideally, it should be possible that robot can communicate with technical systems in a similar way as they do with human assistants [203]. The interconnection of the distributed intelligent subsystems is a key factor in the overall performance of the system. The development of new multi-modal human machine interfaces and new navigation systems are current research robotic trends towards human-oriented robotics [204]. The speed function is proposed such that the minimum cost path between the starting and target locations in the environment is the optimum planned path. The speed function is controlled by one parameter, which takes one of three possible values to generate the safest, the shortest, or the hybrid planned path [205]. The hybrid path is much safer than the shortest path, but shorter than the safest one.

2.8 Summary

This chapter has extensively reviewed the various aspects of the progress made so far in the navigation of mobile robot. First the kinematics and dynamic analysis of differential drive mobile robot has been addressed and the problem of posture regulation, path following, and trajectory tracking have been demonstrated. A stable control algorithm capable of dealing with nonholonomic navigation problems, and that considers the complete dynamics of a mobile robot. This chapter also provides a detailed review report which has been used in last decades by many researchers in the area of new intelligent control technique. The working principle and controllers for navigation of mobile robot using different intelligent controller i.e. Fuzzy Logic controller, Neural Controller, Adaptive Neuro-Fuzzy Controller and Heuristic Rule Base Neural Controller can be outlined for powerful cognition of the complex environment around the robots to distinguish between targets, surrounding obstacles, other moving robots and for cooperative behaviour. From the survey it has been noticed that the mobile robot navigation can be controlled successfully in a complex, unknown and dynamic environments using the above strategies.

❖ Publications

1. "Various strategies of navigation of mobile robot: A review" *International Journal of Automation and Control*, Inderscience, 3(2/3), 2009, 114-134.
2. "Design of Intelligent Controllers for Mobile Robot navigation: A Review" *International Conference on ETEE07*, January12-14, 2007, Science City Kolkata, India.
3. "Navigational Path Analysis of Mobile Robot in various Environments: A survey", *National Conference on ATENM-07*, January 23-24, 2007, BIT Mesra, India.

3 Kinematic Analysis of Mobile Robots

Kinematics is the most basic study of how mechanical systems behave and it plays greater role to follow a desired trajectory. In mobile robotics, it is necessary to understand the mechanical behaviour of the robot both in order to design appropriate mobile robots for tasks and to understand how to create control software of mobile robot hardware. This chapter provides a detailed kinematic analysis of mobile robot.

3.1 Introduction

The kinematics of mobile robot focuses on design of mobile platforms to perform intelligent tasks, rather than on the development of methodologies for analyzing, designing, and controlling the mobility subsystem. Improved mechanical designs and mobility control systems will enable the application of mobile robot to perform the task with smooth movement during navigation. Kinematic methodology is the first step towards achieving these goals. The objective is thus to model the kinematics of mobile robot. Modeling mobile robots with differential drive wheels as control systems may be addressed with a differential geometric point of view by considering only the classical hypothesis of "rolling without slipping". Such a modeling provides directly kinematic models of the robots. Kinematics is the study of the geometry of motion. In the context of mobile robot, this chapter provides to determining the motion of the robot from the geometry of the constraints imposed by the motion of the wheels. In recent years, much attention has been paid to the motion control of mobile robots [206]. However, practically they need to take into account the specific dynamics that can produce the input velocity using wheel torque provided by the mobile robot. Broadly, the mobile guidance robots can be classified into active and passive types. An active mobility assist robot can be controlled using DC motor or servo motors while the user is guided within the environment. A passive mobility assist robot need not have actuators on the wheels but only brakes or the actuators may only steer the wheels. The active robot can perform complicated motions and enhance the overall maneuverability. However, the user’s safety needs to be considered in the development of such mobile assistive robots [207]. Hence, from the safety point of view, passive robots are better than the active robots as the users can exercise their own discretion during motion.

3.2 Type of Wheels used in Mobile Robot

The choice of wheel types for a mobile robot is strongly linked to the choice of wheel arrangement, or wheel geometry. The mobile robot designer must consider these two issues simultaneously when designing the locomotion mechanism of a wheeled robot. The wheel type and wheel geometry require three fundamental characteristics of a robot maneuverability, controllability, and stability. Minimum two numbers of wheels required for static stability. Two-wheel differential-drive robot can achieve static stability if the center of mass is below the wheel axle. Dynamics can also cause a two-wheeled robot to strike the floor with a third point of contact, for instance, with sufficiently high motor torques from standstill. Conventionally, static stability requires a minimum of three wheels, with the additional caveat that the center of gravity must be contained within the triangle formed by the ground contact points of the wheels. Stability can be further improved by adding more wheels, although once the number of contact points exceeds three, the hyper static nature of the geometry will require some form of flexible suspension on uneven terrain.

The most popular robot in research community is the two-wheel differential-drive robot where the two wheels rotate around the center point of the robot and two diametrically opposed wheels (i.e., two parallel conventional wheels, one on each side of the robot). One or two additional ground contact points may be used for stability, based on the application. Mobile robots employing conventional wheels are significantly simpler and more reliable. When it is necessary for a mobile robot to perform operations along a specific path, its ability to accurately track a reference path is a critical performance feature. In general, there are only two independent posture variables during a path tracking process. Therefore, to reach high control performance, the tracking control algorithm must be consistent with the kinematics of the mobile robot [208]. The conventional wheels are the most widely used among wheel mobile robots with wheeled locomotion. These wheels are simple to construct, require less maintenance, provide smooth motion, offer high load carrying capacity and are cheap. Conventional wheels have two degree of freedom. The axis of rolling is orthogonal to the steering axis and the centre of the wheel is at the intersection of these two axes. It allows travel along a surface in the direction of the wheel orientation, and rotation about the point-of-contact between the wheel and the floor shown in Fig. 3.1(a). The rotational degree of freedom is slippage, since the point-of-contact is not stationary with respect to the floor surface. Even though we define the rotational slip as a degree of freedom, we do not consider slip transverse to the wheel orientation a degree of freedom, because the magnitude of force required for the transverse motion is much larger than that for rotational slip. The conventional wheel is by far the most widely used wheel; automobiles, roller skates and bicycles utilise this wheel. Mobile robot built with conventional wheels can be classified into four main groups, (i) based on the way they are driven and steered, namely, (i) differential drives (ii) synchronous drives (iii) tricycle drives and (iv) car-like drives.

The most maneuverable wheel is a ball which possesses three degree of freedom without slip as shown in Fig. 3.1(b). Schemes have been devised for actuating and sensing ball wheels, but generally unaware of any existing implementations. The ball wheels, have the advantages of full mobility, maneuvers from an arbitrary position at non-zero velocity in all directions are possible. They all possess three degree of freedom in the plane with no singularities. One major difficulty concerning robots built around this type of wheel lies in mounting the ball onto the robot chassis while the ball to roll freely in any direction on the floor. Furthermore, dirt and friction also hamper the performance of this type of wheels.

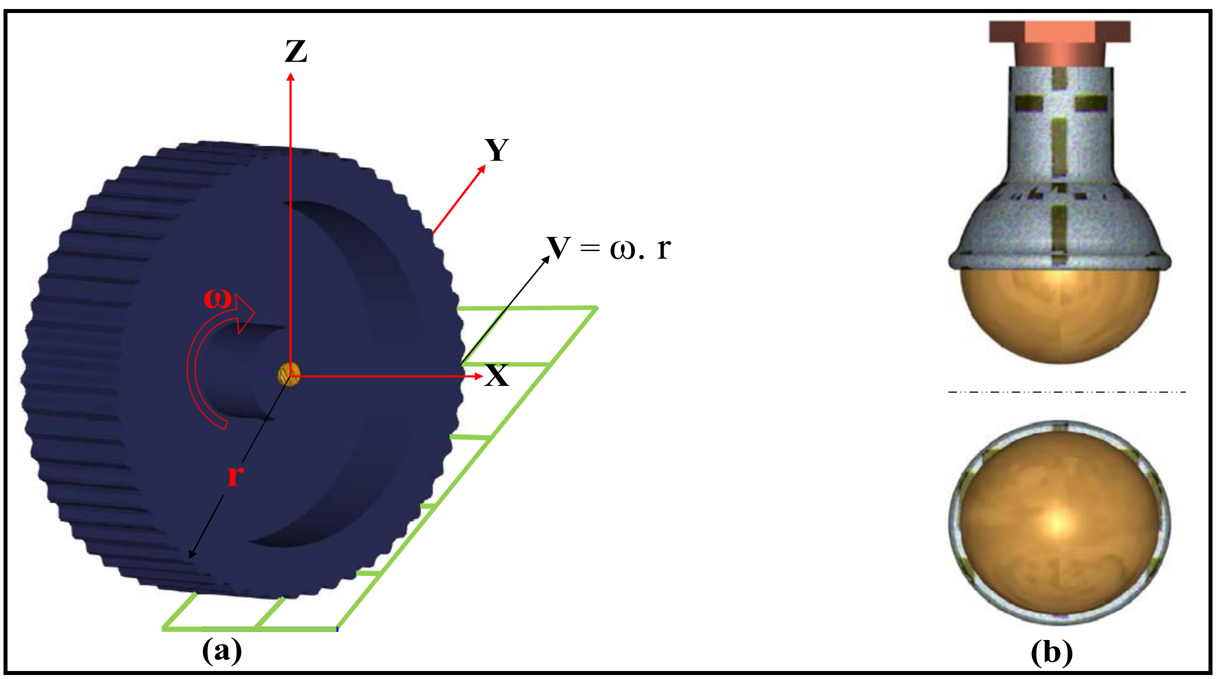


Figure 3.1.(a) Schematic view of conventional wheel and (b) Ball wheel used in mobile robots.

3.3 Analysis of Wheel Kinematic Constraints

The first step to a kinematic model of the robot is to express constraints on the motions of individual wheels. The first constraint enforces the concept of rolling contact that the wheel must roll when motion takes place in the appropriate direction. The second constraint enforces the concept of no lateral slippage, that the wheel must not slide orthogonal to the wheel plane. The fixed standard wheel has no vertical axis of rotation for steering. Its angle to the chassis is thus fixed, and it is limited to motion back and forth along the wheel plane and rotation around its contact point with the ground plane. Fig. 3.2 depicts a fixed standard wheel and indicates its position pose relative to the robot's local reference frame$[x_p, y_p]$. The position of P is expressed in polar coordinates by distance l and angle α. The angle of the wheel plane relative to the chassis is denoted by β, which is fixed since the fixed standard wheel is not steerable. The wheel, which has radius r, can spin over time, and so its rotational position around its horizontal axle is a function of time t: ω and t.

The rolling constraint for this wheel enforces that all motion along the direction of the wheel plane must be accompanied by the appropriate amount of wheel spin so that there is pure rolling at the contact point,

$$[\sin(\alpha+\beta) \; -\cos(\alpha+\beta) \; (-l)\cos\beta]R(\theta).\dot{q} = \dot{\omega}r \tag{3.1}$$

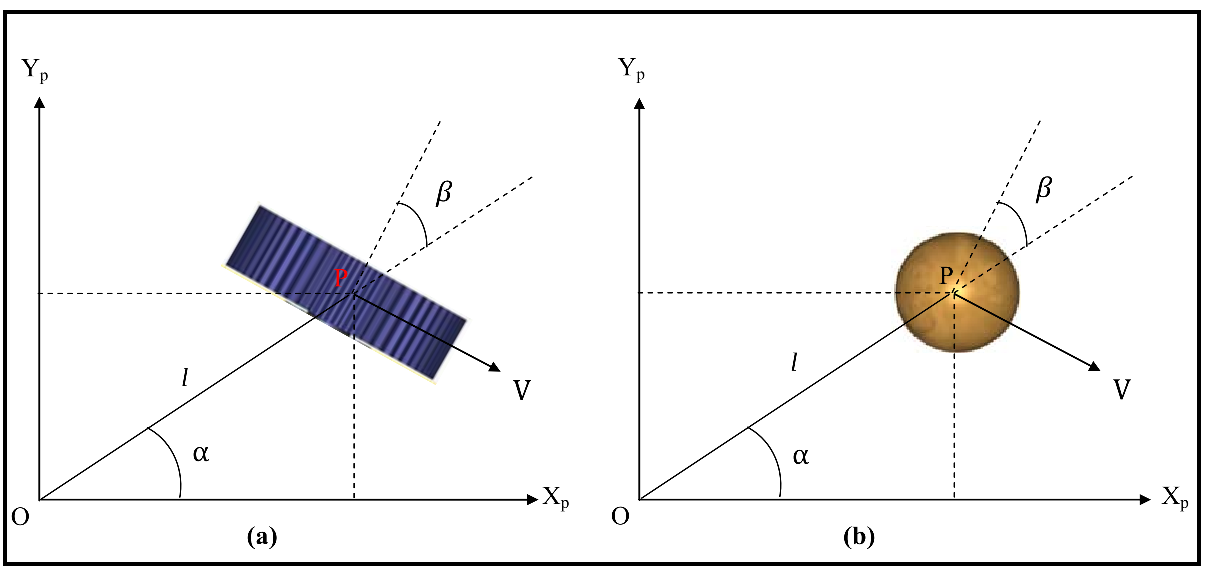


Figure 3.2. Kinematic parameters of (a) Standard wheel (b) Ball wheel.

Where R (θ) is rotation matrix

$$R(\theta) = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3.2}$$

And

$$\dot{q} = \left[\dot{x}\,\dot{y}\,\dot{\theta}\right]^{T} = f(l, r, \theta, \dot{\omega_l}, \dot{\omega_r}) \tag{3.3}$$

The first term of Eq. 3.1, the sum denotes the total motion along the wheel plane. These three elements of the vector on the left represent mappings from each of $\dot{x}$, $\dot{y}$, $\dot{\theta}$, to their contributions for motion along the wheel plane.

Note that the $R(\theta)\dot{q}$ term is used to transform the motion parameters Eq. (3.2) $\dot{q}$ that are in the global reference frame [X, Y] into motion parameters Eq. (3.2) in the local reference frame$\left[x_p\ y_p\right]$. This is necessary because all other parameters in the equation α, β, l, are in terms of the robot's local reference frame. This motion along the wheel plane must be equal, according to this constraint, to the motion accomplished by spinning the wheel, $r.\dot{\omega}$.

The sliding constraint for this wheel enforces that the component of the wheel's motion orthogonal to the wheel plane must be zero,

$$[\cos(\alpha+\beta)\ \ \sin(\alpha+\beta)\ \ l\sin\beta]R(\theta).\dot{q} = 0 \tag{3.4}$$

The ball or spherical wheel, places no direct constraints on motion (Fig. 3.3(b)). Such a mechanism has no principal axis of rotation, and therefore no appropriate rolling or sliding constraints exist. Therefore, Eq. (3.1) simply describes the roll rate of the ball in the direction of motion of point of the robot.

However, the interpretation of Eq. (3.4) is different. The omnidirectional spherical wheel can have any arbitrary direction of movement, where the motion direction given by is a free variable deduced from Eq. (3.4). Consider the case that the robot is in pure translation in the direction of y_p. Then Eq. (3.4) reduces to, $\sin(\theta+\alpha) = 0$, thus, α = - θ, which makes sense for this special case.

3.4 Motion Control

A common task in mobile robotics is to drive the robot to a certain position and orientation as fast as possible given the limits of the static and dynamic properties of the robot setup. Kinematic models and motion-control algorithms for a differential drive has been discussed in this section. A partially compliant frame provides roll and yaw degrees of freedom between the axles. Motion control of nanholonomic mobile robot can sub divided in two methods one is open loop control and another one is close loop control method which have been exhibited in next section.

3.4.1 Open Loop Control

The objective of a kinematic controller is to follow a trajectory described by its position or velocity profile as a function of time. This is often done by dividing the trajectory (path) in motion segments of clearly defined shape, for example, straight lines and segments of a circle. The control problem is thus to pre-compute a smooth trajectory based on line and a circle segment which drives the robot from the initial position to the final position (Fig.3.3 (a)). This approach can be regarded as open-loop motion control, because the measured robot position is not fed back for velocity or position control. It has several disadvantages:

- It is not at all an easy task to pre-compute a feasible trajectory if all limitations and constraints of the robot's velocities and accelerations have to be considered.
- The robot will not automatically adapt or correct the trajectory if dynamic changes of the environment occur.
- The resulting trajectories are usually not smooth, because the transitions from one trajectory segment to another are not smooth (for most of the commonly used segments). This means there is a discontinuity in the robot's acceleration.

3.4.2 Feedback Control

A more appropriate approach in motion control of a mobile robot is to use a real-state feedback controller. With such a controller the robot's path-planning task is reduced to setting intermediate positions (sub goals) lying on the requested path.

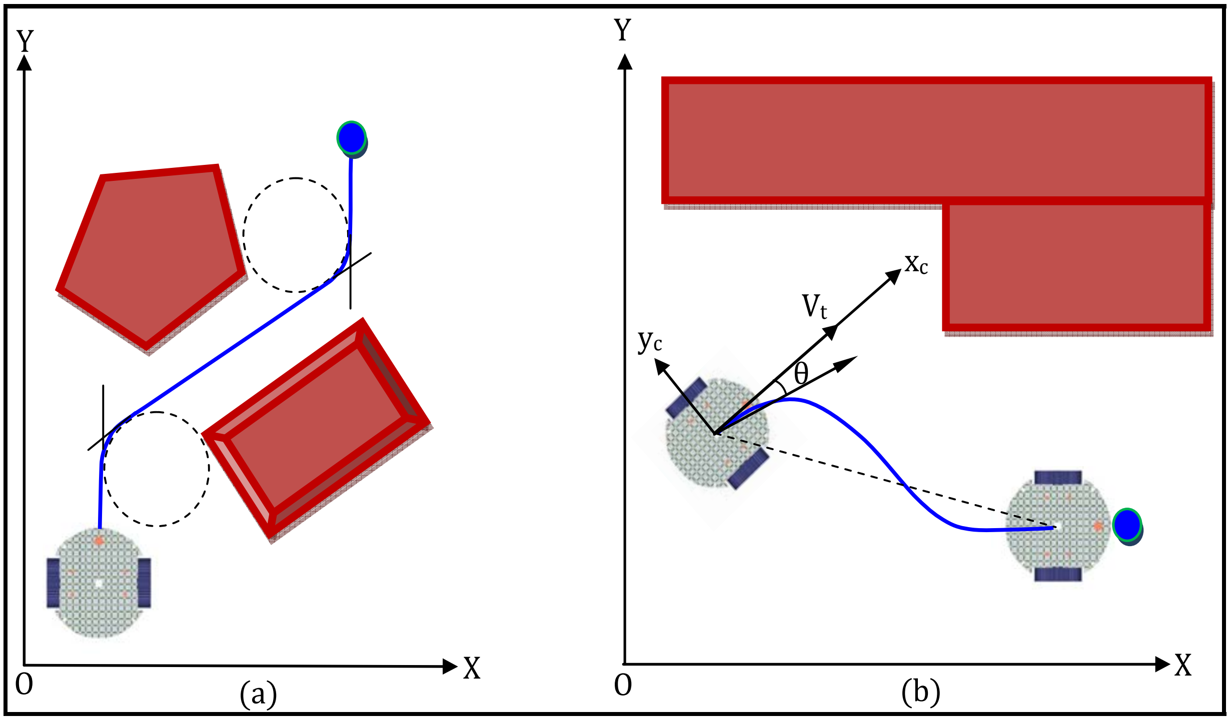


Figure 3.3. Kinematic control of a mobile robot, (a) Open-loop control based on straight lines and circular trajectory segments, (b) Typical situation for feedback control of a mobile robot.

3.5 Problem Statement

Consider the situation shown in Fig. 3.3(b), with an arbitrary position and orientation of the robot and a predefined goal position and orientation. The actual pose error vector given in the robot reference frame $\{x_c\ y_c\ \theta\}$ is e= ${}^{R}[x \quad y \quad \theta]^T$ with X, Y and θ being goal coordinate.

The task of the controller layout is to find a control matrix K, if it exists

$$K = \begin{bmatrix} k_{11} & k_{12} & k_{13} \\ k_{21} & k_{22} & k_{23} \end{bmatrix} \text{ with } k_{ij} = k(t, e) \tag{3.5}$$

Such that the control of V(t) and ω(t)

$$\begin{bmatrix} V(t) \\ \omega(t) \end{bmatrix} = K.\ e = K.\ {}^{R}[x \quad y \quad \theta]^T \tag{3.6}$$

Drives the error 'e' toward zero.

$$\lim_{t\to\infty} e(t) = 0 \tag{3.7}$$

3.6 Kinematic Analysis of Mobile Robot

The kinematics analysis of mobile robot which has been used for experimental validation is analyzed in this section. The driving wheels are independently driven by two actuators (motor 0 and motor 1) to achieve the motion and orientation. All wheels have the same diameter denoted by '2r' as shown in Fig. 3.4. The left and right driving wheels are separated by distance 'W'. The center of gravity (COG) of the mobile robot is located at point 'C'. The point 'P' is located in the intersection of a straight line passing through the middle of the vehicle and a line passing through the axis of the two centre wheels. The distance between points P and C is'd'.

The kinematics of the differential drive mobile robot is based on the assumption of pure rolling and there is no slip between the wheel and surface.

$$V_t = \frac{1}{2}[v_r + v_l] \tag{3.8}$$

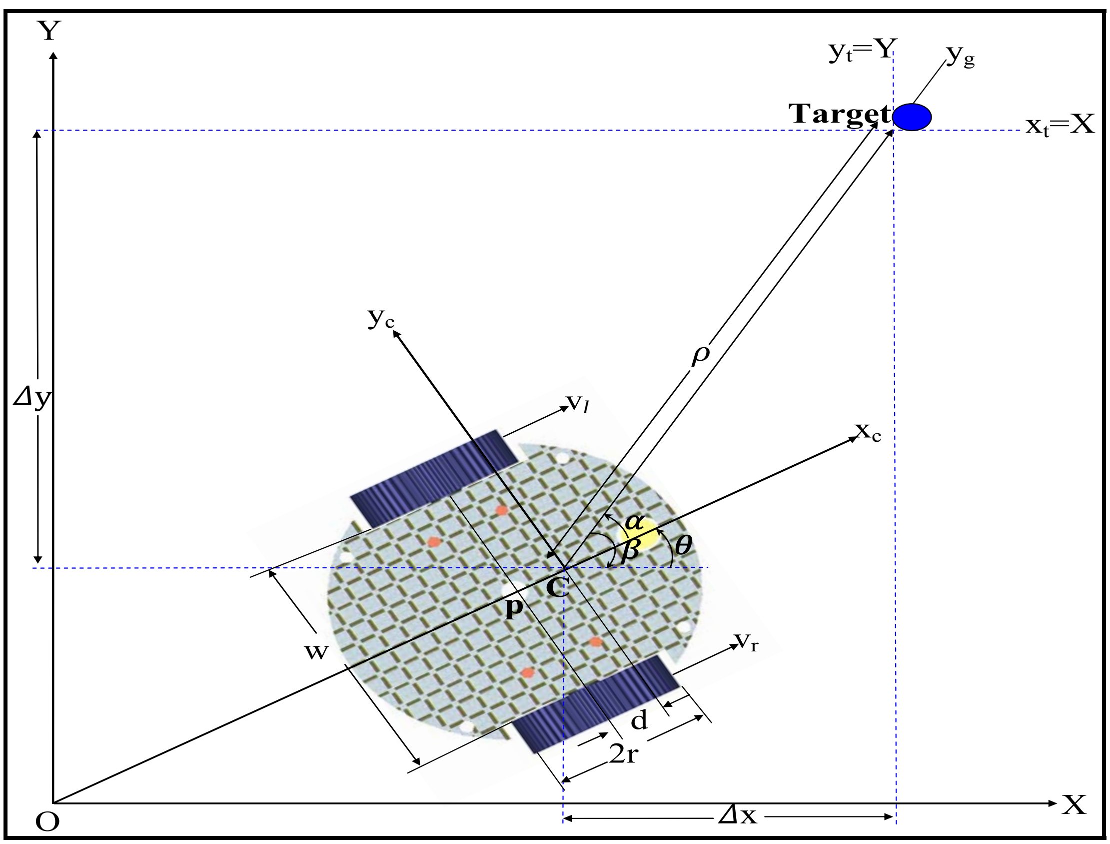


Figure 3.4. Kinematic analysis of mobile robot

$$\omega_t = \frac{1}{W}[v_r - v_l] \tag{3.9}$$

$$v_r = r\omega_r \text{ And } \quad v_l = r\omega_l \tag{3.10}$$

Where

V = linear velocity and

ω = angular velocity of the mobile robot.

Suffix r, *l* and t stand for right, left wheel and tangential (with respect to its center of gravity point 'C' measured in a right wheel) respectively.

The position of the robot in the global coordinate frame (O X Y) is represented by the vector notation as,

$$q = [x_c \ y_c \ \theta]^T \tag{3.11}$$

Where x_c and y_c are the coordinates of the point C in the global coordinate frame (Fig. 3.4). The variable θ is the orientation of the local coordination of the local coordinate frame $(C \ x_c \ \ y_c)$ attached on the robot platform measured from the horizontal axis. Three generalized coordinates can describe the configuration of the robot as Eq. (3.11).

The mobile robot system considered here is a rigid body and the wheels are pure rolling and no slippage. This states that the robot can only move in the direction normal to the axis of the driving wheels. Therefore, the component of the velocity of the contact point with the ground, orthogonal to the plane of the wheel is zero, i.e.

$$\left[\dot{y}_c \cos\theta \ - \dot{x}_c \operatorname{Sin}\theta \ - d\dot{\theta}\right] = 0 \tag{3.12}$$

Let consider all kinematics constraints are independent of time, and can be expressed as,

$$A(q)\,\dot{q} = 0 \tag{3.13}$$

Where, $A(q)$ is the input transformation matrix associated with the constraints, and,

$$C^T(q)\,A^T(q) = 0 \tag{3.14}$$

Where $C(q)$ is the full rank matrix formed by a set of smooth and linearly independent vector fields spanning the null space of $A^T(q)$.

From Eq. (3.13) and Eq. (3.14) it is possible to find an auxiliary vector time function V (t) for all time 't'.

$$\dot{q} = C(q).V(t) \tag{3.15}$$

The constraint matrix in Eq. (3.13) for a mobile robot is given by

$$A(q) = [-\sin\theta \quad \cos\theta \quad -d\,] \tag{3.16}$$

It is easy to verify equations of motion Eq. (3.12) in terms of linear and angular velocity [24]. The matrix C (q) is given by

$$C(q) = \begin{bmatrix} \cos\theta & -d\sin\theta \\ \sin\theta & d\cos\theta \\ 0 & 1 \end{bmatrix} \tag{3.17}$$

And

$$V(t) = [v \quad \omega]^T \tag{3.18}$$

Where 'v' is the maximum linear velocity ($|v| \le V_{max}$) and ω is the maximum angular velocity($|\omega| \le \omega_{max}$) at the point 'p' along the robot axis.

Therefore, the kinematics Eq. in (3.15) can be described as

$$\dot{q} = \begin{bmatrix} \dot{x}_c \\ \dot{y}_p \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & -d\sin\theta \\ \sin\theta & d\cos\theta \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{3.19}$$

Eq. (3.19) is called the steering system of the vehicle. The control problem is to find a suitable control law so that the system can track desired reference trajectories. The control laws are designed to produce suitable left and right wheel velocities for driving the mobile robot to follow required path trajectories. The steering angle (SA) can be computed as,

$$\mathrm{SA} = \frac{V_l - V_r}{w} \tag{3.20}$$

Where V_l and V_r are left and right wheel velocities and w is the wheel base. If $V_l > V_r$ the steering angle is in clockwise direction and if $V_l < V_r$ the steering angle is in counterclockwise direction. The control problem is to find a suitable control law so that the robot can follow desired trajectory.

3.7 Dynamic Analysis of Mobile Robot

The simplified version of the dynamic model used in for differential driven mobile robot. In this simplified model, the mass and the moment of inertia of the two wheels are considered to be negligible compared to those of the robot platform. The Euler–Lagrange equations of motion are used to derive the dynamics of the mobile robot [24]. The dynamical equations of the mobile robot can be expressed as;

$$M(q)\ddot{q} + N(q,\dot{q})\dot{q} + F(\dot{q}) + G(q) = E(q)\tau - A^T(q)\lambda \tag{3.21}$$

Where;

$M(q) \in R^{3nx3n}$ is a symmetric, positive definite inertia matrix assembled from the individual axle module inertia matrices.

$$M(q) = \begin{bmatrix} m & 0 & md\sin\theta \\ 0 & m & -md\cos\theta \\ md\sin\theta & -md\cos\theta & I \end{bmatrix} \tag{3.22}$$

Here, ‘m’ is the mass and ‘I’ is the moment of inertia of the platform.

$N(q,\dot{q}) \in R^{3nx3n}$ is the centripetal and coriolis forces,

$$N(q,\dot{q}) = \begin{bmatrix} 0 & 0 & md\dot{\theta}\cos\theta \\ 0 & 0 & md\dot{\theta}\sin\theta \\ 0 & 0 & 0 \end{bmatrix} \tag{3.23}$$

$F(\dot{q}) \in R^{3nx1}$ denotes the surface friction,

$$F(\dot{q}) = 0 \tag{3.24}$$

$G(q) \in R^{3nx1}$ is the gravitational vector, which is zero, because the trajectory of the mobile base is constrained to horizontal plane,

$$G(q) = 0 \tag{3.25}$$

$E(q) \in R^{nx1}$ is the input transformation matrix,

$$E(q) = \frac{1}{r}\begin{bmatrix} \cos\theta & \cos\theta \\ \sin\theta & \sin\theta \\ w/2 & -w/2 \end{bmatrix} \tag{3.26}$$

Here, 'r' is radius of the wheel and 'w' is distance between the two wheels.

$\tau \in R^{2nx1}$is the input torques,

$$\tau = \begin{bmatrix} \tau_r \\ \tau_l \end{bmatrix} \tag{3.27}$$

Here, τ_r and τ_l represent right and left wheel torques, respectively.

$A(q) \in R^{nx3n}$ is the global matrix associated with the nonholonomic constraints from Eq. (16),

$$A^T(q) = \begin{bmatrix} -\sin\theta \\ \cos\theta \\ -d \end{bmatrix} \tag{3.28}$$

And, $\lambda \in R^{2nx1}$is the vector of Lagrange multipliers associated with the constraint,

$$\lambda = -m(\dot{x}_c \cos\theta + \dot{y}_c \sin\theta)\dot{\theta} \tag{3.29}$$

By differentiating Eq. (3.15), one gets,

$$\ddot{q} = \dot{C}(q)V(t) + C(q)\dot{V}(t) \tag{3.30}$$

Substituting all value, using Eq. (3.15), multiplying both side of C^T in Eq. (3.21) and using the property of equation, the robot dynamics Eq. (3.21) can be transformed into a more appropriate representation for control purposes.

$$\overline{M}\dot{v} + \overline{N}v = E\tau \tag{3.31}$$

Where, $\overline{M} = C^T MC$, $\overline{N} = C^T(M\dot{C} + NC)$, and $\overline{E} = C^T E$.

By neglecting the Eq. (3.21) and Eq. (3.31) it is assumed that there is "perfect velocity tracking" than the Eq. (3.19) is applicable for velocity command. However, it is necessary for perfect velocity tracking using the computed torque control as exhibited Eq. in (3.21). One can obtain the necessary control 'τ' for Eq. (3.31) which guarantees perfect velocity tracking using the computed torque control as given in Eq. (3.21). To implement Eq. (3.21) or Eq. (3.31) explanation of mathematics involved for analysis the robot dynamics is necessary for perfect velocity tracking of mobile robot.

3.8 Motion Control of Mobile Robot

In Fig. 3.4, let $\propto$ denote the angle between the x_c axis of the robot's reference frame fixed with the robot y_c and the vector connecting the centre of the axel of the wheels with the final position y_g. When $I_1 = \left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$, $\propto \epsilon I_1$. (3.32)

In polar coordinates (see Fig. 3.4) the error is now [209],

$$\rho = \sqrt{\Delta x^2 + \Delta y^2} \tag{3.33}$$

$$\propto = -\theta + \tan^{-1}\left(\frac{\Delta y}{\Delta x}\right) \tag{3.34}$$

$$\beta = -\theta - \alpha \tag{3.35}$$

This yields a system description, in the new polar coordinates, using a matrix equation

$$\begin{bmatrix} \dot{\rho} \\ \dot{\alpha} \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} -\cos(\alpha) & 0 \\ \frac{\sin\alpha}{\rho} & -1 \\ -\frac{\sin\alpha}{\rho} & 0 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{3.36}$$

Where ρ = distance between the center of the robot's wheel axel and the target position. On other hand, when $I_2 = [(-\pi, -\pi/2) \cup (-\pi/2, \pi)]$, $\propto \epsilon\, I_2$. (3.37)

Refining the forward direction of the robot by setting $v = -v$, the system described by a matrix equation will be:

$$\begin{bmatrix} \dot{\rho} \\ \dot{\alpha} \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} -\cos(\alpha) & 0 \\ -\frac{\sin\alpha}{\rho} & 1 \\ \frac{\sin\alpha}{\rho} & 0 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{3.38}$$

The coordinates transformation is not defined at x = y = 0, as such a point the determinant of the Jacobian matrix of the transformation is not defined, that is unbounded. For $\alpha \in I_1$ forward direction of the robot points towards the target. For $\alpha \in I_2$ it is the reverse direction. By properly defining the forward direction of the robot at its initial configuration, it is always possible to have $\alpha \in I_1$ at $t = 0$. However, this does not mean that α remains in I_1 for all time t. Hence, to avoid that the robot changes direction during approaching the target, it is necessary to determine, if possible, the controller in such a way that $\alpha \in I_1$ for all t, whenever $\alpha(0) \in I_1$. The same applies for the reverse direction.

The control problem is to find a suitable control law so that the system can track desired reference trajectories. The control laws are designed to produce suitable left and right wheel velocities for driving the mobile robot to follow required trajectory path.

3.8.1 The control Law

The control signals v and ω must now be designed to drive the robot from its actual configuration, Say $(\rho_0 \quad \alpha_0 \quad \beta_0)$ to the target position. It is obvious that Eq. (3.36) presents a discontinuity at $\rho = 0$, and it does not obstruct smooth stability [209].

If we consider now the linear control law

$$v = k_\rho \rho \tag{3.39}$$

$$\omega = k_\alpha \alpha + k_\beta \beta \tag{3.40}$$

We get with Eq. (3.36) a closed-loop system described by

$$\begin{bmatrix} \dot{\rho} \\ \dot{\alpha} \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} -k_\rho \rho \cos(\alpha) \\ k_\rho \sin\alpha - k_\alpha \alpha - k_\beta \beta \\ -k_\rho \sin\alpha \end{bmatrix} \tag{3.41}$$

The system does not have any singularity at $\rho = 0$ and has a unique equilibrium point at$(\rho, \alpha, \beta) = (0, 0, 0)$. Thus it will drive the robot to this point, which is the target position. In the Cartesian coordinate system the control law Eq. (3.40), leads to equations which are not defined at $x = y = 0$. The angles are expressed in the range $(-\pi, \pi)$. The control signal v has always a constant sign, that is, it is positive whenever $\alpha(0) \in I_1$ and it is always negative otherwise. This implies that the robot performs its parking maneuver always in a single direction and without reversing its motion.

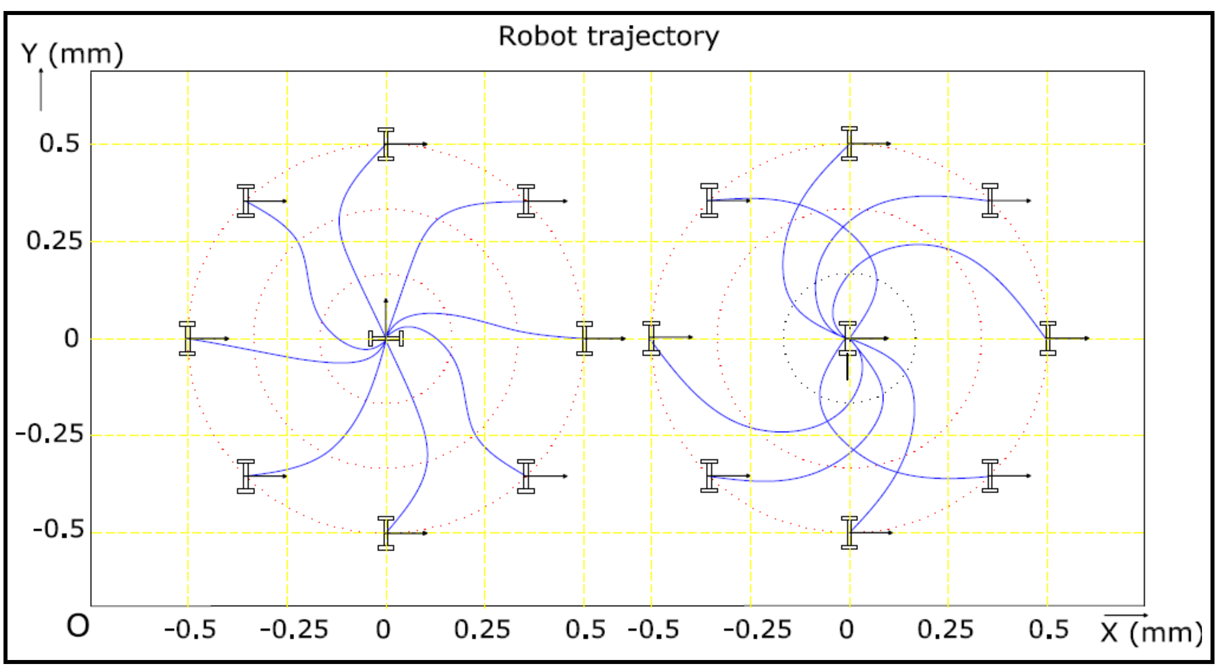


Figure 3.5. Resulting paths of the robot at initially on the unit circle in X-Y plane.

Fig. 3.5 shows the resulting paths when the robot is initially on a circular path in the X, Y plane. All movements are smooth trajectories toward the target in the center. The control parameters for this simulation are set to

$$k = (k_\rho \quad k_\alpha \quad k_\beta) = (3, 8, -1.5) \tag{3.42}$$

3.8.2 Local Stability Issue

It can further be shown, that the closed-loop control system Eq. (3.41) is locally exponentially stable [209] if

$$k_\rho > 0,\ k_\beta > 0,\ k_\alpha - k_\rho > 0 \tag{3.43}$$

By linearising around the equilibrium $(\cos\alpha = 1, \sin\alpha = \alpha)$ position, Eq. (3.41) can be written as,

$$\begin{bmatrix} \dot{\rho} \\ \dot{\alpha} \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} -k_\rho & 0 & 0 \\ 0 & -(k_\alpha - k_\rho) & -k_\beta \\ 0 & -k_\rho & 0 \end{bmatrix} \begin{bmatrix} \rho \\ \alpha \\ \beta \end{bmatrix} \tag{3.44}$$

Hence, locally exponentially stable if the Eigen values of the matrix have a negative real part. The characteristic polynomial of the matrix A is

$$A = \begin{bmatrix} -k_\rho & 0 & 0 \\ 0 & -(k_\alpha - k_\rho) & -k_\beta \\ 0 & -k_\rho & 0 \end{bmatrix} \tag{3.45}$$

$$(\lambda + k_\rho)\left(\lambda^2 + \lambda(k_\alpha - k_\rho) - k_\rho k_\beta\right) = 0 \tag{3.46}$$

Eq. 3.46 has all roots with negative real part if it holds the following condition

$$k_\rho > 0,\ -k_\beta > 0,\ k_\alpha - k_\rho > 0 \tag{3.47}$$

This Eq. (3.47) gives the stability condition. The condition given in the above expression provides the local stability.

The following conditions ensure that the robot does not change the direction during its approach to the target along with the stability condition [209].

$$k_\rho > 0, \quad k_\beta < 0, \quad k_\alpha + \frac{5}{3}k_\beta - \frac{2}{\pi}k_\rho > 0 \tag{3.48}$$

This implies that $\alpha \in I_1$ for all t, whenever $\alpha(0) \in I_1$ and $\alpha \in I_2$ for all t, whenever $\alpha(0) \in I_2$ respectively. This strong stability condition has also been verified in applications.

3.9 Summary

In this chapter the problem of exponential stabilization of the kinematic and dynamic model of a differential drive mobile robot has been developed. The proposed dynamic controller can track the desired velocity, which is generated by kinematic controller, without exact knowledge about the dynamic model of a mobile robot. With the help of developed methodology, the robot can achieve path following as well as velocity tracking, considering both kinematic model and dynamic model of the mobile robot. The details of kinematics and dynamics of mobile robot is addressed and solved using a discontinuous, bounded, time invariant, state feedback control law. The exact knowledge about the parameter values required to track the desired velocity, which is generated by kinematic controller. It has been seen using the above stability condition the robot exponentially converges to the goal position. Moreover, the derivation of a stabilizing controller for the dynamic model allows a direct implementation of the proposed control law on real systems. Numerical results were presented and the stability of the system was verified. Simulation results verify the theoretical conjecture and expose the flaws in ignoring the dynamics of the mobile robots.

❖ Publications

1. "Navigational path analysis of mobile robots using ANFIS controller in dynamic environment", *Journal of Mechanical Engineering Science part C*, IMechE, 2009, (Accepted).
2. "Heuristic rule base hybrid neural network for navigation of mobile robot", *Journal of Engineering Manufacture part B*, IMechE, 2009, (Accepted).
3. Path optimisation of mobile robot using artificial neural network (ANN) controller, *International Journal of System Science*, Taylor & Francis, 2009, (Accepted).

4 Analysis of Fuzzy Logic Controller for Mobile Robot

An autonomous mobile robot is a machine that operates in an unknown and unpredictable environment. A key issue in the research of an autonomous mobile robot is the design and development of a control technique that enables the robot to navigate in a real world environment, avoiding structured and unstructured obstacles especially in crowded and unpredictably changing environment. This chapter presents the development in the area of intelligent controller for mobile robot in various (known and unknown) environments. Action coordination of the behaviours will be addressed using fuzzy logic in the present research. The inputs to the proposed fuzzy control scheme consist of a target angle between a robot and a specified target and the distances between the robot and the obstacles to the left, front, and right to its locations, being acquired by an array of sensors. In this chapter an intelligent controller has been proposed for mobile robot navigation algorithm employing fuzzy theory in a complex cluttered environment.

4.1 Introduction

It is observed that the human beings do not need precise, numerical information input to make a decision, but they are able to perform highly adaptive control. Humans have a remarkable capability to perform a wide variety of physical and mental tasks without any explicit measurements or computations. Examples of everyday tasks are parking a car, driving in city traffic, playing golf, and summarizing a story. In performing such familiar tasks, humans use perceptions of time, distance, speed, shape, and other attributes of physical and mental objects [210]. Fuzzy logic is a problem-solving control system methodology that lends itself for implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, workstation-based data acquisition and control systems. The theory of fuzzy logic systems is inspired by the remarkable human capability to operate on and reason with perception-based information. The rule-based fuzzy logic provides a scientific formalism for reasoning and decision making with uncertain and imprecise information. It can be implemented in hardware, software, or a combination of both. Fuzzy logic approach to control problems mimics how a person would make decisions. The main advantages of a fuzzy navigation strategy lie in the ability to extract heuristic rules from human experience, and to obviate the need for an analytical model of the process [67, 81].

The development of techniques for autonomous navigation in real-world environments constitutes one of the major trends in the current research on robotics. An important problem in autonomous navigation is the need to cope with the large amount of uncertainty that is inherent of natural environments. Fuzzy logic has features that make it an adequate tool to address this problem. Navigation of mobile robots in presence of static and moving obstacles using fuzzy technique is presented in this work. At first, a set of navigation rules are extracted from the data base. The rules are used to control the navigation of mobile robots. The use of fuzzy logic techniques for controlling wheel-based mobile robots has been effectively proposed by many authors in the last decade [6, 67, 86, 154]. This chapter proposes an on-line path analysis and planning approach that embeds a fuzzy strategy to drive a mobile robot. A new intelligent fuzzy interface system has been developed in this current investigation. In this approach, the fuzzy logic system is used to control the robot taking inputs from various sensors. Sensor signals are fed to the fuzzy logic system, and the output provides motor control commands (e.g., turn right or left). The fuzzy logic system learns the full dynamics of the mobile robot online. Fuzzy controller for mobile robot has four inputs and two outputs. Both inputs and output have three membership functions. Each membership function consists of trapezoidal and triangular membership functions. In this methodology 81 rules have been used to design the fuzzy controller. This research focuses a fuzzy logic framework to be implemented in the mobile robot for behaviour design and coordination. The proposed method has been compared with other methods [6, 86, 154, 211] which show the effectiveness of the developed method. It is also concluded that the current method can be successfully employed for navigation of mobile robot. This fuzzy controller of mobile robot for path analysis and planning has been authenticated by experimental verification.

This chapter organized into five sections following the introduction, the entire behaviour of mobile robot is described in section 4.2. The simulation results are discussed in section 4.3. In section 4.4, experimental results are verified with simulation to demonstrate the superiority of the proposed methodology and comparison has been made with other methods [6, 86, 154, 211]. Finally summary is discussed in section 4.5.

4.2 Fuzzy Logic Behaviour for Control Technique

The first and most common application of fuzzy logic techniques in the domain of an autonomous mobile robot is the use of fuzzy control to implement individual behaviour units. Fuzzy logic controllers incorporate heuristic control knowledge in the form of if-then rules and are a convenient choice when a precise linear model of the system to be controlled cannot be easily obtained. Fuzzy logic has features that are particularly attractive in light of the problems posed by autonomous robot navigation. Fuzzy logic allows the modeling of different types of uncertainty and imprecision, building robust controllers starting from heuristic and qualitative models, and integrating symbolic reasoning and numeric computation in a natural framework [2]. Fuzzy controller helps autonomous mobile robot in navigating to a desired location.

Fuzzy logic behaviour control architecture is implemented using fuzzy rule-base and inference engine. Depending on the type of action, from a set of inputs different fuzzy rule bases are activated and hence the corresponding outputs. The output parameters from the fuzzy rule-bases for all actions are same i.e. the velocities of the left and right wheels of the robot, which drive the robot to a desired posture. The fuzzy rules control the steering of the robot according to whether there are obstacles or targets around it and how far they are from it. Because this information is usually not known precisely, fuzzy logic is an appropriate technique for handling it [6]. An Intelligent Fuzzy controller for mobile robot enables the robot to avoid the obstacle and improve target seeking ability. The inputs to the proposed fuzzy control scheme consist of a target angle between a robot and a specified target and the distances between the robot and the obstacles to the left, front, and right locations, acquired by an array of sensors. The outputs from the control scheme are commands for the speed control unit of two side wheels of the mobile robot. The input signals of fuzzy controller are the distances between the robot and obstacles to the left, front, and right locations as well as the target angle between the robot and a specified target, as shown in Fig. 4.1(a) and Fig. 4.1(b). As the robot perceives the target from the image sensor, it computes the difference in angle with respect to global coordinate system between its current position and the target. And get the angle between the robot current moving direction and the target [212]. When the target is located at the left sides of the mobile robot, target angles (tar-ang) are negative and if the target is located to the right side of the mobile robot, the target angles (tar-ang) is defined as positive.

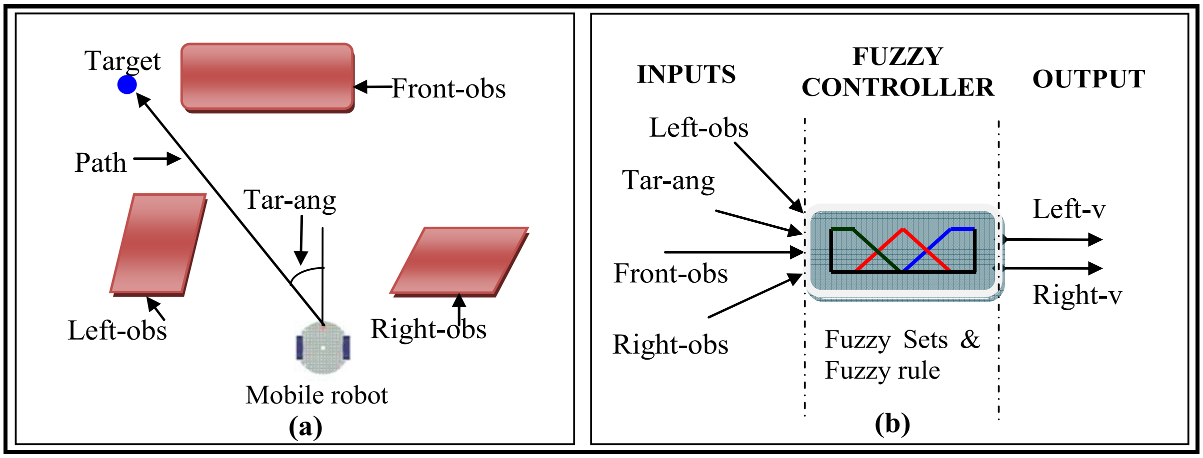


Figure 4.1. Simulation resulting paths of mobile robot.

According to acquired range information by sensors, reactive behaviours are weighted by the fuzzy logic algorithm to control the velocities of the two driving wheels of robot. The basic configuration of a fuzzy system consists of four principal elements: fuzzifier, fuzzy rule base, fuzzy inference engine, and defuzzifier. The fuzzifier is a mapping from the observed crisp input space to the fuzzy sets defined in, the fuzzy set defined is characterized by a membership function and is labeled by the linguistic variables near, medium and far and these are chosen to fuzzify left obstacle distance (left-obs), right obstacle distance (right-obs) and front obstacle distance (front-obs). The linguistic variables positive (P), zero (Z) and negative (N) are used to fuzzify tar-ang and the linguistic variables slow, med. (medium) and fast (Table 4.1). These are used to fuzzify the velocities of the left wheel (left-v) and right wheel (right-v), respectively [86].

Table 4.1. Parameter for variables

Left obstacle distance(left-obs) Right obstacle distance(right-obs) Front obstacle distance(front-obs)	Near(meter)	Medium(meter)	Far (Meter)
	0.0 to 0.6	0.3 to 0.9	0.6 to 1.2
Target angle (tar-ang)	Negative	Zero	Positive
	-60^0 to 0^0	-30^0 to $+30^0$	0^0 to 60^0
Left wheel velocity(Left-v) Right wheel velocity(Right-v)	Slow (m/s)	Medium (m/s)	Fast (m/s)
	0 to 2	1 to 3	2 to 4

The fuzzy rule base is a set of linguistic rules in the form of "if a set of conditions are satisfied, then a set of consequences are inferred." For four inputs two outputs fuzzy system, the general fuzzy rule base may consist of the following.

If "matching degree of x_1 is $\mu_A(x_1)$ and matching degree of x_2 is $\mu_A(x_2)$ and matching degree of x_3 is $\mu_A(x_3)$ and matching degree of x_4 is $\mu_A(x_4)$" Then "matching degree of v_l is $\mu_A(y_i)_l$ and matching degree of v_r is $\mu_A(y_i)_r$".

The matching degree of final output is computed by the following formula.

$$Maching\ degree\ \mu_A(y_i)_{l,r} = min\{\mu_A(x_1), \mu_A(x_2), \mu_A(x_3)\ and\ \mu_A(x_4)\} \qquad (4.1)$$

Where, i = (1, 2, 3,……n), x_1, x_2, x_3, x_4 are the sensor inputs of left, right, front obstacle distance and target angle respectively, $\mu_A(x_1), \mu_A(x_2), \mu_A(x_3)\ and\ \mu_A(x_4)$ are the matching degree of corresponding sensor inputs, and $\mu_A(y_i)_l,\ \mu_A(y_i)_r$ are the inferred inputs matching degree of corresponding left and right wheel velocity.

When the matching degree is one the inferred conclusion is identical to the rule's consequence and if it is zero no conclusions can be inferred from the rule.

Finally the output firing area of the left wheel velocity and right wheel velocity value can be computed by following formula.

$$\mu_A(y_i)_{l,r} = max\{\mu_A(x_1), \mu_A(x_2), \mu_A(x_3)\ and\ \mu_A(x_4)\} \qquad (4.2)$$

The final output (crisp value) of the fuzzy logic controller of left wheel velocity and right wheel velocity can be calculated by

$$Left\ and\ right\ wheel\ Velocity = V_{l,r} = \frac{\sum_{i=0}^{n} \mu_A\ (y_i) \times (z_i)}{\sum_{i=0}^{n} \mu_A(y_i)} \qquad (4.3)$$

Where, $\mu_A(y_i)_{l,r}$ is the firing area of left and right wheel velocity for ith rule, z_i is the centroid distance of the area, n is the total number of parameter, and $V_{l,}\ V_{r,}$ = Velocity of left and right wheel respectively.

In order to reach a specified target in a complex environment, the mobile robot at least needs the following reactive behaviours: 1. Obstacle avoidance, 2. Wall following and 3.Target steer. In this case, a set of fuzzy logic rules is used to describe the reactive behaviours mentioned above. Now, the last part of fuzzy rules from the rule base is to explain, in principle, how these reactive behaviours are realized.

4.3 Behavioural Architecture

One of the major sensor based approaches to mobile robot control is the behaviour architecture. The term behaviour comes from biology and refers to the reaction of an agent to a given situation. Therefore, a behaviour in a mobile robot navigation system usually represents a concern of the robot such as follow the path or avoid obstacle. Behaviour-based architecture helps to decompose control systems into subsystems with task achieving behaviours. A nonholonomic mobile robot (Appendix-C.1) has been designed according to the behaviour-based approach. Kinematics constraint in two dimensional work spaces is discussed in section 3.5. Each robot has four wheels. Two front supported ball wheels which are free and two side middle wheels are powered by separate DC gear servo motors. Each robot has an image and an array of infrared sensors for measuring the distances of obstacles around it, and the bearing of the target and a radio system for communicating with other robots. The information's being sent among the robots are (a) their positions, (b) how far they are from the target, and (c) whether reached the target or not. According to the information acquired by the robots using their sensors, some of the fuzzy control rules are activated accordingly. The outputs of the activated rules are combined and defuzzyfied to get the velocities of the driving wheels of the robots. For the velocities of the left wheel and right wheel of each robot the abbreviations such as *left-v* and *right-v* are used respectively. The above membership functions consist of trapezoidal and triangular. The parameters defining the function are listed as shown in Fig. 4.2. These parameters can be used to generate different fuzzy rules, for example.

Rule: If *(left-obs is far and right-obs is medium and front-obs is near and tar-ang is N)* Then *(left-v is slow and right-v is medium).*

By fuzzy reasoning and the centroid defuzzification method, Rule related to the obstacle avoidance wall-following and target seeking behaviours, is weighted to determine an appropriate control action, i.e., the velocities, left-v and right-v, of the robot's side wheels as shown in Fig. 4.3, the values of the parameters are decided empirically.

4.3.1 Obstacle Avoidance

When the acquired information from the sensors shows that there exist obstacles nearby robot, it must reduce its speed to avoid obstacles. When a robot is close to an obstacle, it must change its speed and steering angle to avoid the obstacle. Mobile robot is able to avoid static as well as dynamic obstacle. If more than one robot is present in the environment, then a robot treats other robots as dynamic obstacles, simulation result shown in Fig. 4.5(a). The fuzzy rules used for obstacle avoidance and motion control by the robots are listed in Table 4.2 as rules 1–27. All the rules in the table are obtained heuristically. Figure 4.3 shows a typical fuzzy controller scenario for obstacle avoidance. The surface view has been shown in Fig. 4.4.

When the robot sense obstacle near to it or the robot moves at curved and narrow roads, it must reduce its speed to avoid collision with obstacles. In this case, its main reactive behaviour is decelerating for obstacle avoidance. This gives the first and second of fuzzy logic rules for realizing this behaviour as follows.

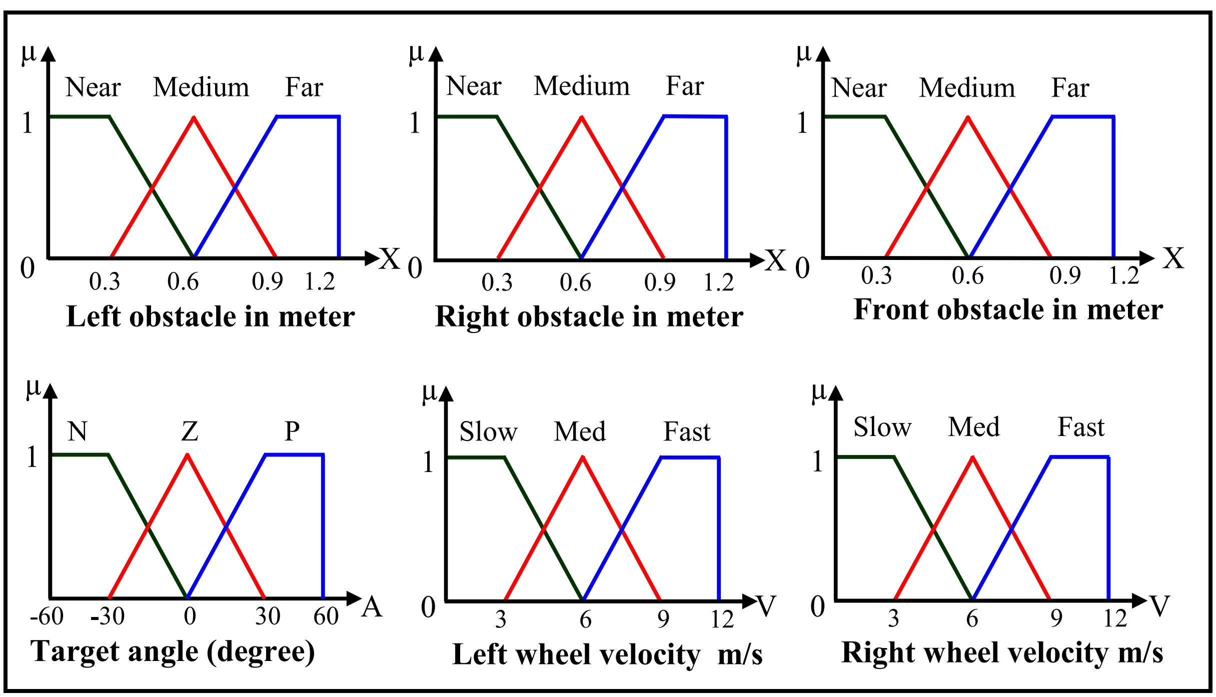


Figure 4.2. Fuzzy membership functions used to design fuzzy logic controller.

Table 4.2. List of rules for obstacle avoidance

RuleNo.	Action	Left-obs	Right-obs	Front-obs	Tar-ang	Left-v	Right-v
1.	AO	Near	Near	Near	Any	Slow	Fast
2.	AO	Near	Near	Medium	Any	Slow	Slow
3.	AO	Near	Near	Far	Any	Med	Med
4.	AO	Near	Medium	Near	Any	Med	Slow
5.	AO	Near	Medium	Medium	Any	Med	Slow
6.	AO	Near	Medium	Far	Any	Fast	Med
7.	AO	Near	Far	Near	Any	Fast	Slow
8.	AO	Near	Far	Medium	Any	Med	Slow
9.	AO	Near	Far	Far	Any	Fast	Med
10.	AO	Medium	Medium	Near	Any	Slow	Fast
11.	AO	Medium	Medium	Medium	Any	Slow	Slow
12.	AO	Medium	Medium	Far	Any	Fast	Fast
13.	AO	Medium	Near	Near	Any	Slow	Fast
14.	AO	Medium	Near	Medium	Any	Slow	Med
15.	AO	Medium	Near	Far	Any	Slow	Med
16.	AO	Medium	Far	Near	Any	Med	Slow
17.	AO	Medium	Far	Medium	Any	Med	Fast
18.	AO	Medium	Far	Far	Any	Fast	Med
19.	AO	Far	Near	Near	Any	Slow	Med
20.	AO	Far	Near	Medium	Any	Med	Fast
21.	AO	Far	Near	Far	Any	Med	Fast
22.	AO	Far	Medium	Near	Any	Slow	Fast
23.	AO	Far	Medium	Medium	Any	Slow	Med
24.	AO	Far	Medium	Far	Any	Med	Fast
25.	AO	Far	Far	Near	Any	Slow	Fast
26.	AO	Far	Far	Medium	Any	Fast	Med
27.	AO	Far	Far	Far	Any	Fast	Fast

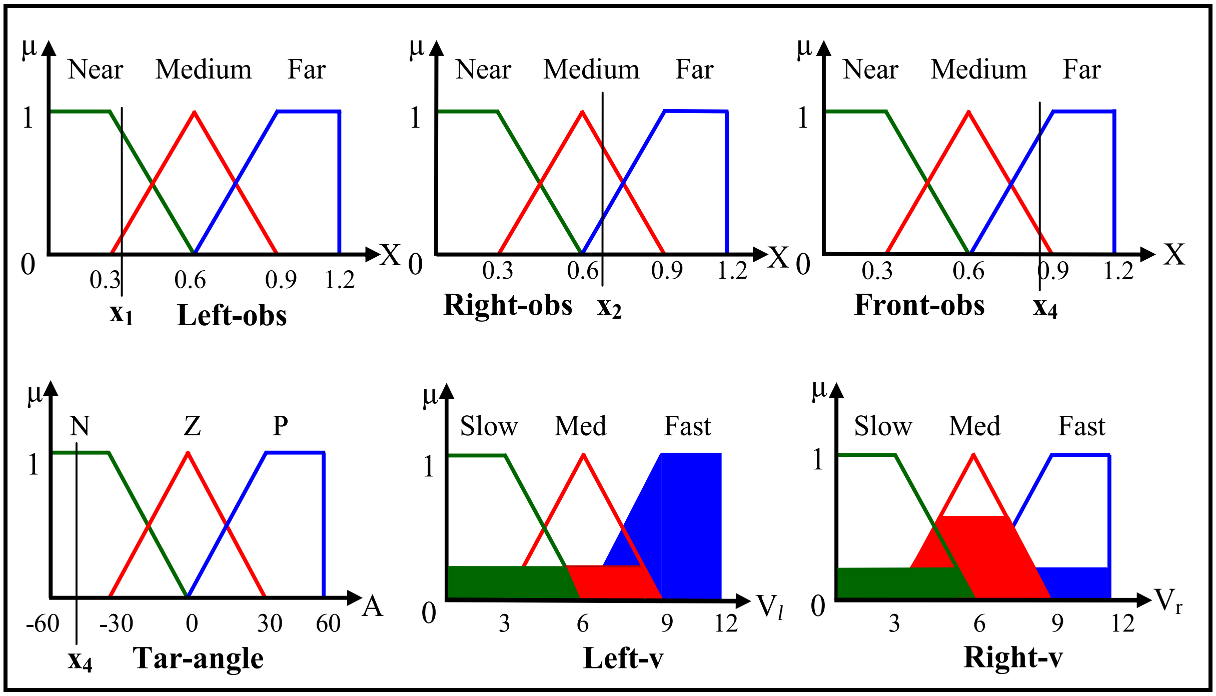


Figure 4.3. Schematic diagram of the fuzzy logic for navigation of mobile robots.

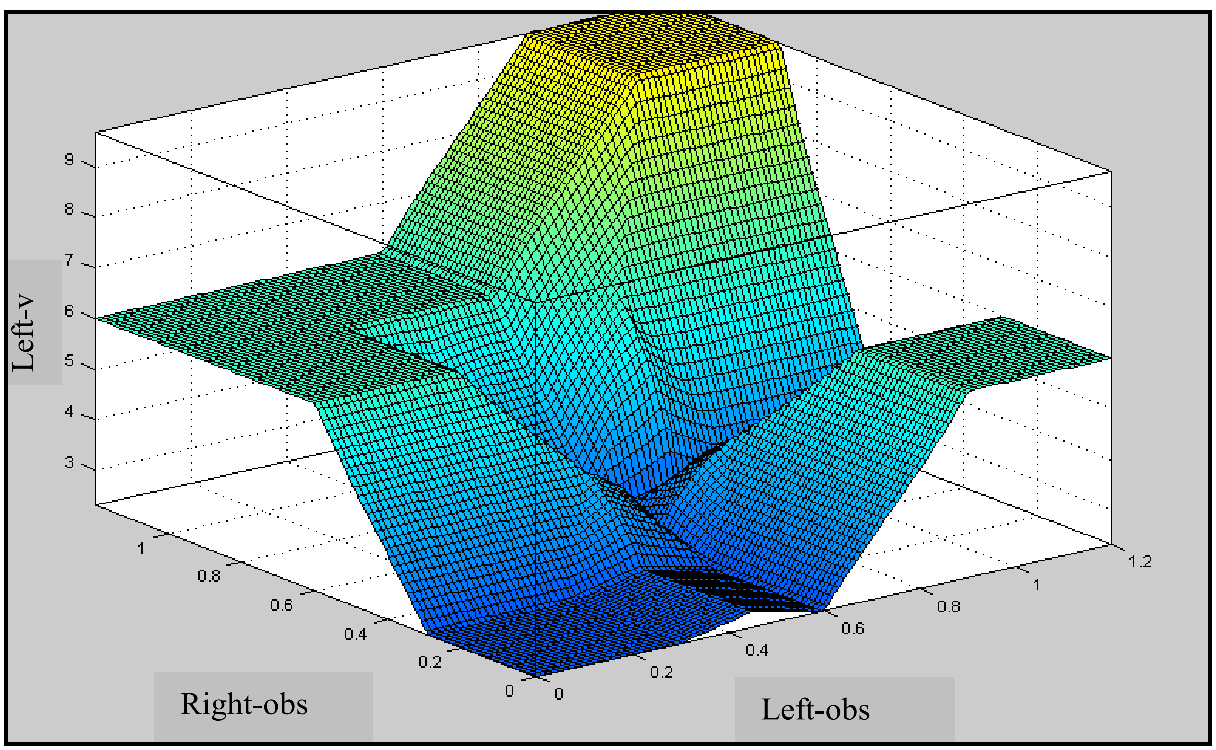


Figure 4.4. The surface view of the fuzzy logic for navigation of mobile robots.

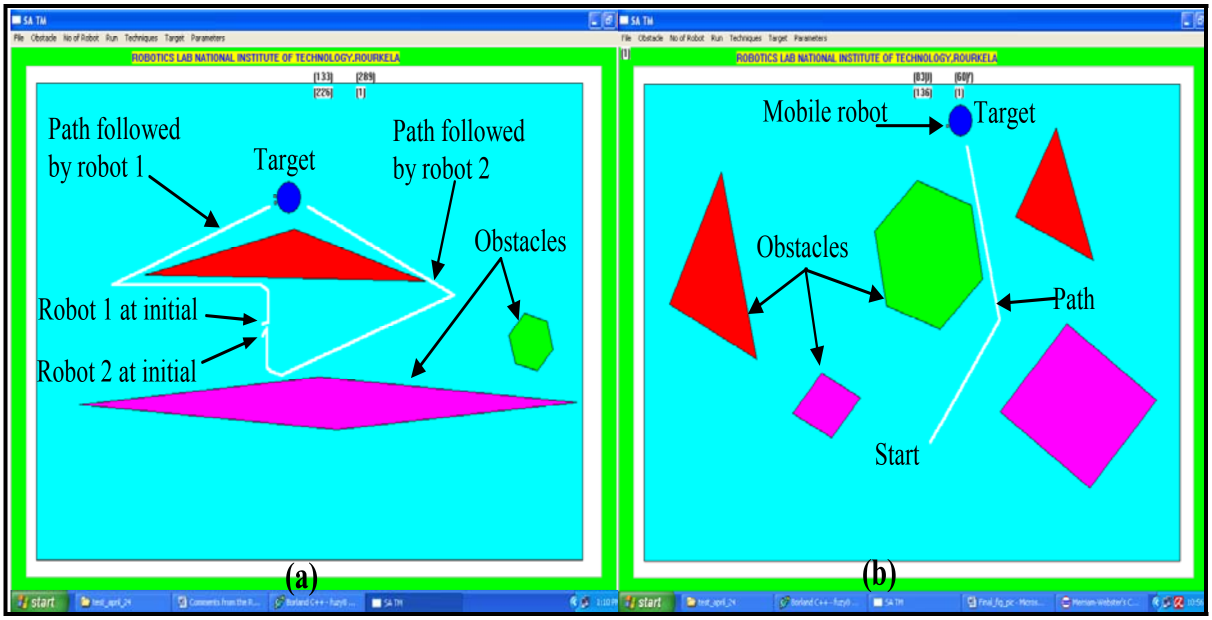


Figure 4.5. (a) Static as well as dynamic obstacle avoidance (b) Obstacle avoidance and motion control behaviour.

If (left-obs is near and right- obs is near and front-obs is near and tar-ang is any) Then (left-v is slow and right-v is fast).

If (left-obs is near and right- obs is near and front-obs is medium and tar-ang is any) Then (left-v is slow and right-v is slow).

Such fuzzy rules represent that the robot only pays attention to obstacle avoidance and moves accordingly to the listed rule in Table 4.2 when it is close to obstacles or at curved and narrow roads. The Simulation result of static as well dynamic obstacle avoidance has been exhibited in Fig. 4.5(a) and Fig. 4.5(b).

4.3.2 Wall Following Behaviour

The wall following behaviour mode will be adopted when the mobile robot detects an obstacle in the front while it is moving towards target along the left or right side of the wall, the mobile robot may turn left or right because presence of obstacle in the front. When the robot moves through a large U-shaped obstacle, at the initial stage, it runs directly towards the target, since the obstacles sensed are far away from it. Then, it makes a left turn, to avoid the obstacles situated at the direct front. As the target is located at the right side of the robot, the behaviour of the approaching target tries to make it turn to the right. As a result, it moves into the right, and the target orientation increases gradually. When the robot reaches the right side it tries to avoid obstacles (the right wall) and approach the target, so it turns to the left. On the basis of the preceding analysis, it will return to the left side. Consequently, the robot travels along the indefinite loop in this concave trap as shown in Fig. 4.6 (a).

To avoid this loop, the robot must have the wall-following behaviour as shown in Fig. 4.6 (b). When the robot is moving to a specified target through a narrow channel, or escaping from a U shaped wall or dead end obstacle specific fuzzy rules for wall following behaviour (Table 4.3) are activated. In the absence of wall following behaviour, the robot is incapable of reaching the goal position when its encounters U shaped or dead end obstacles on their path. In the absence of the wall-following behaviour, the robot is incapable of reaching the goal position.

The simulation result of wall following has been shown in Fig. 4.6 (b) and escaping from dead end obstacle has been shown in Fig. 4.7 (a). For rules 28 and 29 the antecedent and consequent will be.

If (left-obs is far and right- obs is far and front-obs is near and tar-ang is any) Then (left-v is med and right-v is slow).

If (left-obs is far and right-obs is medium and front-obs is near and tar-ang is any) Then (left-v is slow and right-v is med).

Table 4.3. List of rules for wall following behaviour

RuleNo.	Action	Left-obs	Right-obs	Front-obs	Tar-ang	Left-v	Right-v
28	FE	Far	Far	Near	Any	Med	Slow
29.	FE	Far	Medium	Near	Any	Slow	Med
30.	FE	Medium	Far	Near	Any	Fast	Med
31.	FE	Near	Far	Medium	Any	Fast	Med
32.	FE	Near	Far	Near	Any	Fast	Med
33.	FE	Near	Medium	Far	Any	Med	Slow

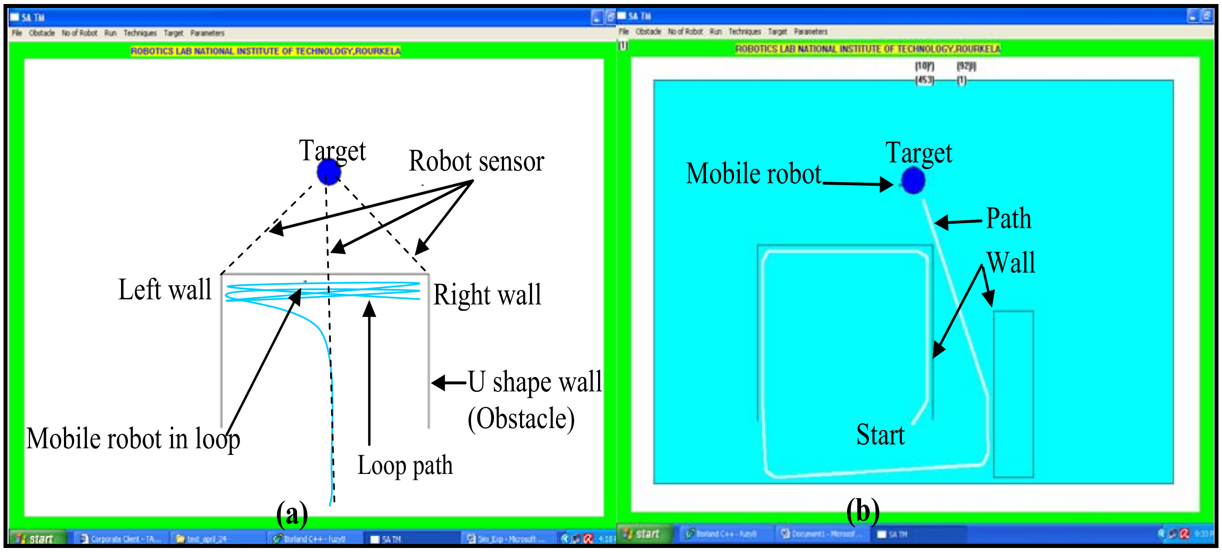


Figure 4.6. (a) Robot in indefinite loop in concave trap (b) Wall following behaviour.

These fuzzy rules show that the robot shall follow wall or an edge of an obstacle when the obstacle is very close to the right or left of the robot, and the target also is located to the right or left. The wall following behaviour depends on a target angle between the robot and a specified target. Wall following behaviour helps the robot to move in one room to another room as well as to escape dead end or find door of typical room, the simulation result shown in Fig. 4.6(b).

4.3.3 Target seeking Behaviour

When the acquired information from the sensors shows that there are no obstacles around robot, its main reactive behaviour is target steering. The simulation results for target steer and map localization is shown in Fig. 4.7 (b), by following the rule from Table 4.4 (i.e. rules 34, 35 and 36).

If (left-obs is far and right-obs is far and front-obs is far and tar-ang is P) Then (left-v is fast and right-v is med).

If (left-obs is far and right-obs is far and front-obs is medium and tar-ang is N) Then (left-v is med and right-v is fast).

If (left-obs is far and right-obs is far and front-obs is far and tar-ang is Z) Then (left-v is fast and right-v is fast).

Table 4.4. List of rules for target seeking and map localisation

RuleNo.	Action	Left-obs	Right-obs	Front-obs	Tar-ang	Left-v	Right-v
34	TS	Far	Far	Far	P	Fast	Med
35	TS	Far	Far	Med	N	Med	Fast
36	TS	Far	Far	Far	Z	Fast	Fast
37	TS	Far	Far	Med	P	Slow	Med
38	TS	Far	Med	Far	N	Med	Fast
40	TS	Med	Far	Far	Z	Fast	Fast

These fuzzy logic rules show that the robot mainly adjusts its motion direction and moves towards the target. Generally, the weights of the behaviours, obstacle avoidance, and target steer depend largely on the distances between the robot and the obstacles to the left, front, and right locations. When the robot reaches the local target, it stops and waits for the other robot to reach the target for further coordinated action at their end. The position of the robots is communicated between each other in the perception model through radio modems. By this communication, each robot knows the position of other robots present in that environment. When the robot gets lost, it tries to make contact with other robots and those robots try to locate the lost robot by a coordinated action. If a robot is lost, it tries to undo its movement until it is within the preview of other robots present in that environmental scenario.

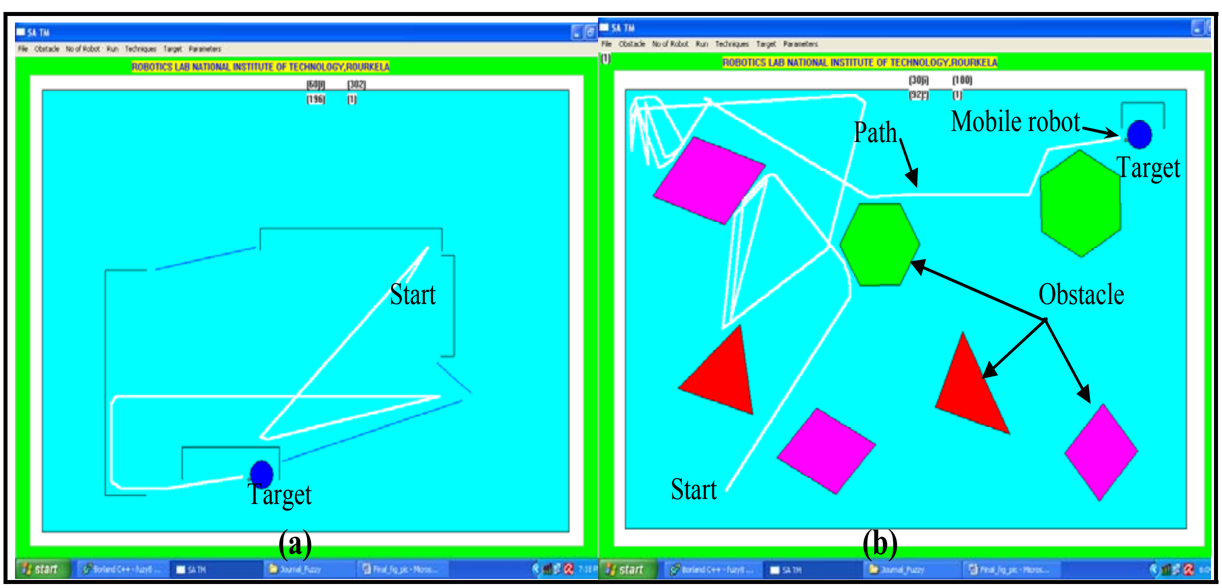


Figure 4.7. (a) Escape from dead ends and find the target (b) Target seeking behaviour.

4.4 Simulation Results and Discussion

The series simulation tests have been conducted with the ROBNAV software (Appendix-A). To demonstrate the effectiveness and the robustness of the proposed method, simulation results on mobile robot navigation are exhibited in various environments. In the proposed control strategy, reactive behaviours are formulated by fuzzy sets and fuzzy rules, and these fuzzy rules are integrated in one rule base. In most of the literatures, the simulation study is carried out for path-tracking [86], goal-finding, and avoid-static obstacle only.

In this chapter, a new intelligent controller has been proposed for mobile robot navigation using fuzzy logic. It is more efficient than the other traditional reactive behaviour control and also easier to design and implement. The navigation algorithm has better reliability and real-time response because perception, localization, cognition, and motion-control decision units are integrated in one module and are directly oriented to a dynamic environment. The simulation results show that the proposed method, using information acquired by infrared sensors, can perform robot navigation in complex and uncertain environments. The results from the proposed fuzzy controller for mobile robot have been compared with the result from adaptive controller by Das et al. [86] for path tracking shown in Fig. 4.8. In addition, a comparison has been done between the results obtained using the controller developed by Zhu et al. [154] and results from the current developed controller. The comparisons show a good agreement (shown in Fig. 4.9).

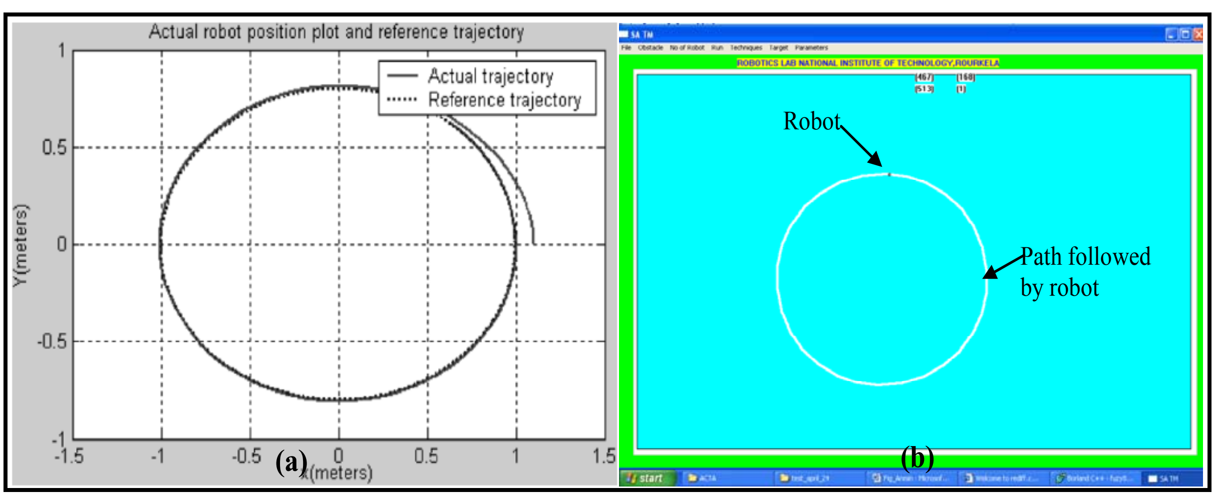


Figure 4.8. (a) Mobile robot reference trajectories by Das et al. [86] (b) Mobile robot reference trajectories by proposed controller.

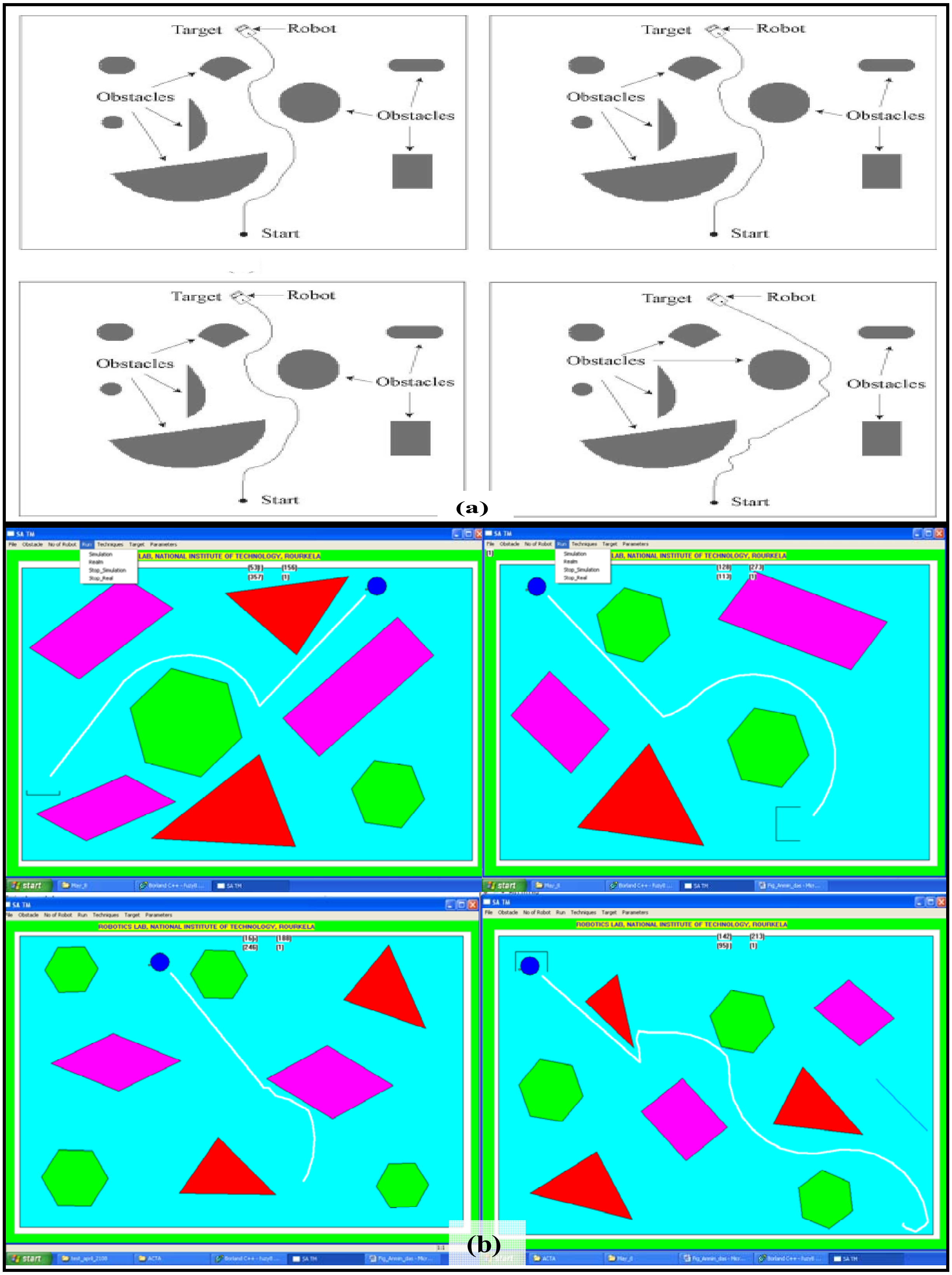


Figure 4.9. (a) Mobile robot trajectories with different number by Zhu et al. [154] (b) Mobile robot trajectories with different number by purposed method.

4.5 Experimental results

In order to exhibit the effectiveness of the proposed fuzzy controller for mobile robot, the simulation results are verified with experimental results, comparison is also done between the results from Adaptive fuzzy logic-based controller by Das et al. [86] and neuro-fuzzy based approach by Zhu et al. [154]. The comparison of controllers with the current developed controller, demonstrate the feasibility of the current approach (discussed in section 4.4.). It is found that the developed fuzzy controller can negotiate the obstacles efficiently. Moreover, the developed controller can be used for several mobile robots.

The experimental results have been conducted by loading the software into the developed mobile robot in the robotics laboratory. The assumptions about the mechanical structure and motion of a mobile robot, to which the proposed method is applied, are as follows.

1. The mobile robot consists of rigid base fitted with DC gear servomotor and wheels are connected to motor shaft.
2. The mobile robot moves on a plane surface (on lab specified floor area).
3. The wheel of a mobile robot rolls on the floor without any translational slip.
4. The wheel of a mobile robot makes rotational slip at the contact point between each wheel and the floor.

The experimental paths followed by mobile robots to reach the target are obtained as shown in Fig. 4.10(a), Fig. 4.10(b), and Fig. 4.10(c). From the fuzzy controller (inputs: left, front, right obstacle distances, and target angle) after defuzzification, robots get the left and right wheel velocities, which subsequently give the new steering angles. The paths traced by the robots are marked on the floor by a pen (fixed to the front of the robots) as they move (Fig. 4.10 (c)). The experimentally obtained paths follow closely those traced by the robots during simulation (shown in Fig. 4.11). From these figures, it can be seen that the robots can indeed avoid obstacles and reach the targets. Table 4.5 shows the times taken by the robots in simulations and in the experimental tests to find the targets. The figures given are the averages of 12 experiments on each environmental scenario being conducted in the laboratory. These robotics behaviours have been verified in simulation and experimental modes.

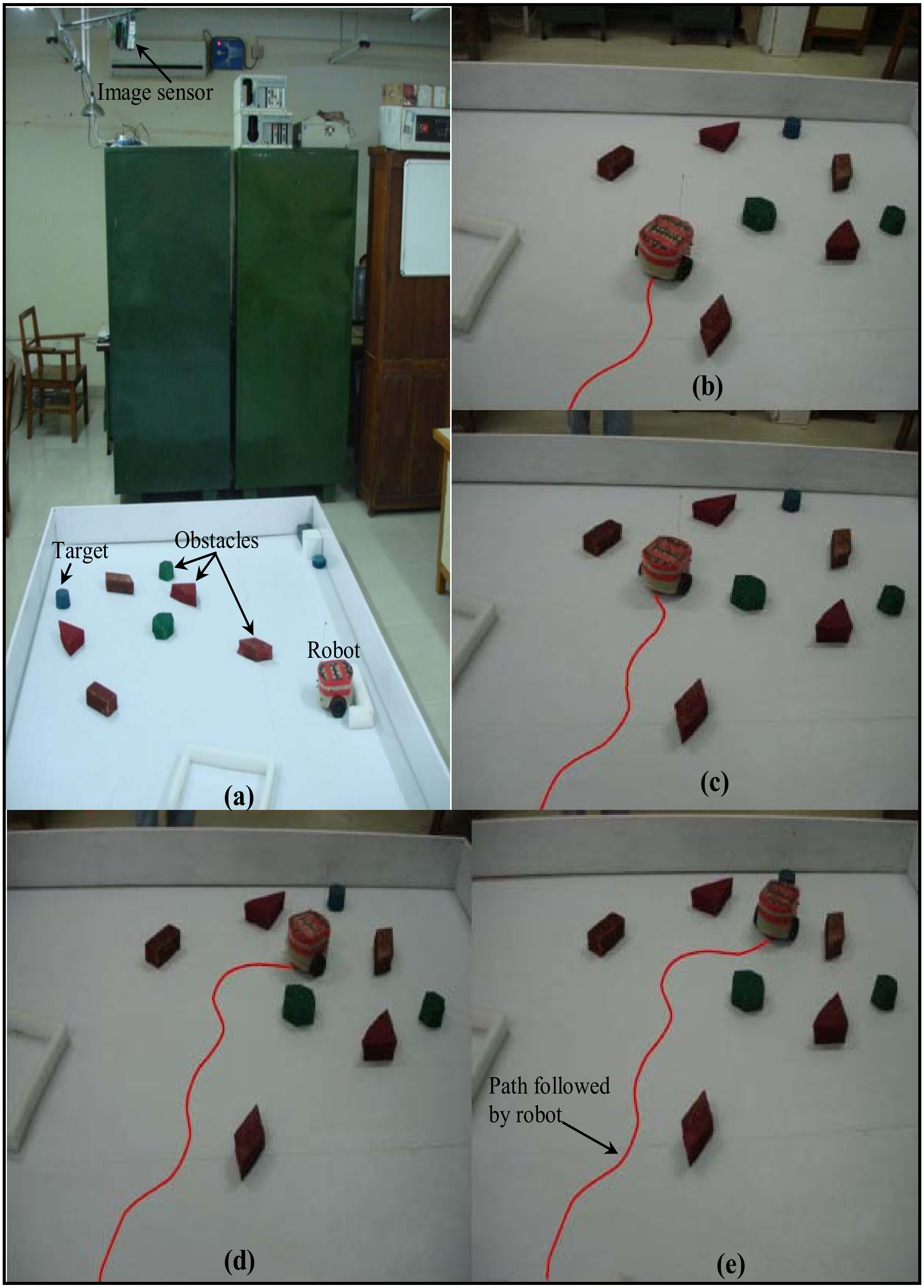


Figure 4.10. Experimental results of mobile robot to reach the target successfully.

Table 4.5. Time taken by robots in simulation and experiment to reach targets

S. No.	Average of 12 experiments in each environment	Time during simulation(sec.)	Time during experiment(sec.)	Percentage of error (%)
01.	For 1st environment scenario	17.37	19.5	12.26 %
02.	For 2nd environment scenario	17.37	19.7	13.41 %
03	For 3rd environment scenario	17.37	19.5	12.26 %

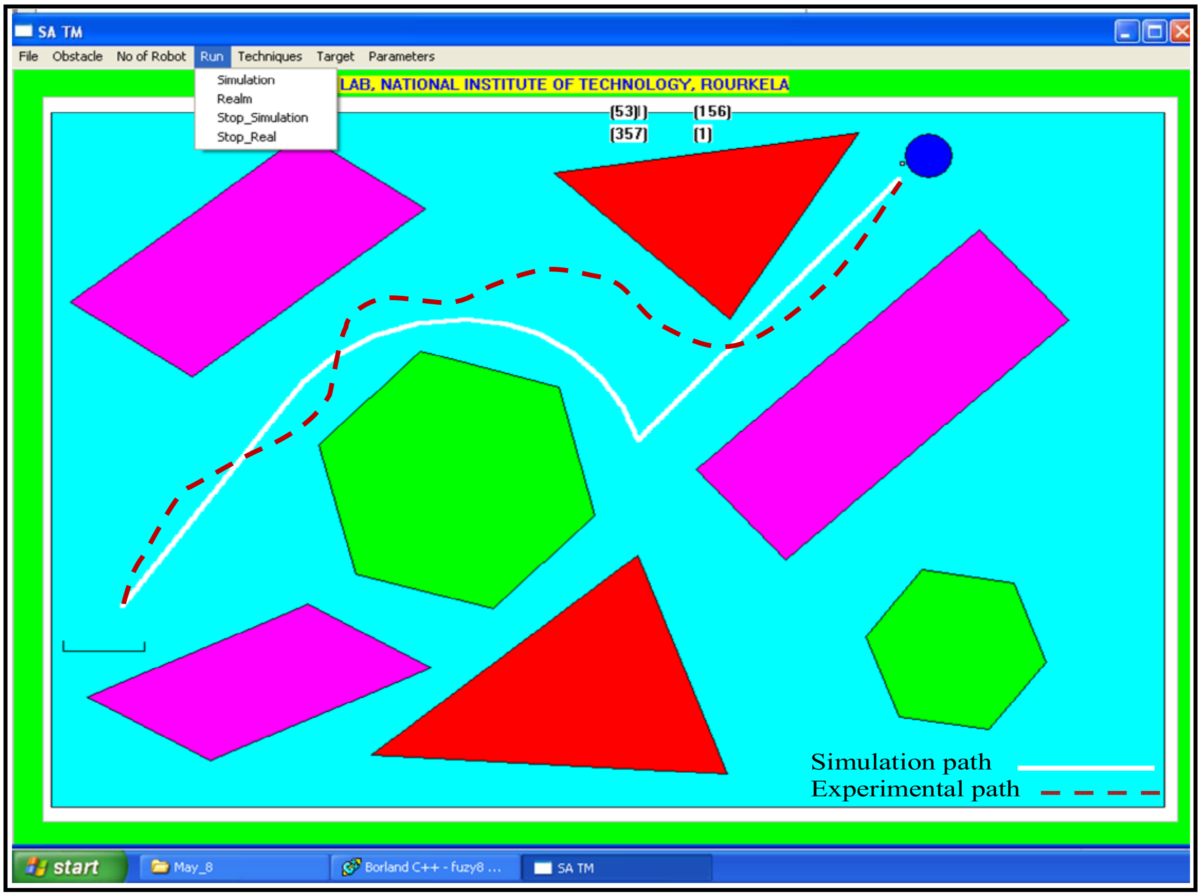


Figure 4.11. Experimental results validation with simulation mode.

It is observed that the robots are able to reach the targets efficiently during simulation and experiment, which demonstrate the feasibility of this approach.

4.6 Summary

From the above theoretical, analytical, simulation and experimental results, the following conclusions are drawn for the present investigation.

1. The robots are able to navigate successfully in a cluttered environment using the developed fuzzy controller.
2. With the help of the developed fuzzy inference technique, the robots are able to recognise the environment and reach the target successfully. This has been demonstrated in simulation and experimental results.
3. The fuzzy rules outlined give a navigational control strategy, which indirectly address the question of determining the sequence of action to achieve the goal.
4. To verify the theoretical analysis a simulated environment has been developed by embedding the fuzzy controller.
5. The experimental results obtained during the navigation of real mobile robots are compared with the simulation results. A good agreement has been seen during comparison. This shows the authentication of the developed intelligent fuzzy controller.
6. This navigation strategy can be used in a mobile robot working in hazardous conditions, for cooperative task, unmanned space missions.
7. Various navigational control strategies (e.g. obstacle avoidance, wall-following action, and target seeking) have been addressed in the current developed controller. These behaviours are shown in different simulation and experimental scenarios.

❖ Publications

1. "Intelligent fuzzy interface technique for controller of mobile robot", *Journal of Mechanical Engineering Science part C*, IMechE, 222 (1), 2008, 2281-2292.
2. "Fuzzy controller for path analysis and planning of mobile robot" *International Journal of Robotics and Automation*, ACTA, conditionally accepted for publication. Revised version submitted.
3. "Intelligent controller for autonomous mobile robot" *International conference on ICMAG-08*, December, 6-12, 2008, Goa (IIT Mumbai), India.
4. "Design of Fuzzy controller for path analysis and planning of autonomous mobile robot" *International conference of ICSCIS-07*, December 27-29, 2007, JEC Jabalpur, India.
5. "Fuzzy logic controller for autonomous mobile robot" *International conference on RTIME-07*, October 5-6, 2007, UCE Ujjain, India.
6. "Path Analysis of Mobile Robot using Fuzzy logic", *National Conference on TSDPS-07*, January 6-7, 2007, IT GGDU Bilaspur, India.
7. Navigation of mobile robot: Fuzzy logic Approach", *22nd National Convention of Production Engineers & National Conference*, Jun2-3 2007, Institution of Engineers(India), Jabalpur, India.
8. "Navigation of mobile robot using fuzzy logic" *Geominetech symposium on ENTMS-07*, May 11-12, 2007, Bhubneshwar, India.

5 Analysis of Neural Controller for Mobile Robot

This chapter provides a novel approach for design of an intelligent controller for autonomous mobile robot using multilayer feed forward neural network which enables the robot to navigate in a real world dynamic environment. The inputs to the proposed neural controller consist of left, right, and front obstacle distance with respect to its position and target angle. The output of the neural network is steering angle. A four layer neural networks has been designed to solve the path and time optimisation problem of mobile robots that deals with the cognitive tasks such as learning, adaptation, generalisation and optimisation. Back propagation algorithm is used to train the network. The simulation results are compared with experimental results, which are satisfactory and show a very good agreement. The training of the neural nets and the control performances analysis of the neural network has been done in a real experimental setup.

5.1 Introduction

A lot of research is going on around the globe to find a suitable intelligent control to be used for navigation of mobile robot without human interaction. One of the most important issues in the design and development of intelligent controller for mobile robot is the navigation problem, i.e. the sequences of actions required during goal achieving without collision with static as well as dynamic obstacle. This consists of the abilities of a mobile robot to plan and execute collision free motions within its environment. However, this environment may be imprecise, vast, dynamical and either partially or non-structured. Bio-inspired robotics, in this context, tries to give an answer to the issues like mimicking, the behaviours and the structure of living creatures in the controller of the mobile robot. The bio-inspired neural controller is based on the working principal of nervous system of simple animals, like arthropods or invertebrates and can be used to control mobile robot. This chapter proposed a biologically inspired neural network approach for real-time collision-free motion planning of mobile robots in real world dynamic environment. The necessary requirements of the mobile robot is tracking and reaching the given target by avoiding static as well as dynamic obstacles. This is the main research area being addressed in this chapter. The path and time optimisation of mobile robot depends on the intelligence of the controller. Many researchers used various methods to optimise the path and time. Their proposed methods are complicated and they may good for local path planning but not for global path planning. The developed method is simple and obtained results depicts that the method is efficient and effective for navigation of mobile robot in dynamic cluttered environment. Four layer perceptron neural networks have been used to design an intelligent controller. The first layer is used as input layer, which directly read signals from the arrays of sensors. The input of the network is front obstacle distance, right obstacle distance, left obstacle distance and target angle. The neural network is consisting of two hidden layer, which adjust the weight of neurons. The output layer provides steering angle of the robot. Back propagation algorithm is used to minimise the error and optimise the path and time of mobile robot to reach the target.

The outline of this chapter is as follows, following the introduction, the neural network architecture for navigation of mobile robot is presented in section 5.2. The simulation results are discussed and to prove feasibility of the developed methodology a comparison has been made with other methods [194, 213, 214] in section 5.3. In section, 5.4 experimental results are verified with simulation to demonstrate the superiority of the proposed methodology. Finally, summary has been discussed in the last section 5.5.

5.2 Analysis of Neural Network for Navigation

Artificial neural networks consist of a set of simple, densely interconnected processing units. These units transform signals in a non-linear way. Neural networks are non-parametric estimators, which can fit smooth functions based on input-output examples. The neural network used is a four-layer perceptron [215]. The numbers of layers are found empirically to facilitate training. The input layer has four neurons, three for receiving the values of the distances from obstacles in front and to the left and right of the robot and one for the target bearing. If no target is detected, the input to the fourth neuron is set to zero. The output layer has a single neuron, which produces the steering angle to control the direction of movement of the robot. The numbers of neurons are found based on the number of training patterns and the convergence of error during training to a minimum threshold error. Two hidden layers are used, as with one hidden layer there is difficult in training the neural network within a specified error limit. The training error is the difference between desired output and actual output. The first hidden layer has ten neurons and the second hidden layer has three neurons. These numbers of hidden neurons were also found empirically.

Fig. 5.1 depicts the neural network with its input and output signals. The neural network trained to navigate by presenting it with 200 patterns representing typical scenarios, some of which are depicted in Fig. 5.2. For example, Fig. 5.2 (b) shows a robot is advancing towards an obstacle, another obstacle being on its right hand side. There are no obstacles to the left of the robot and no target within sight. The neural network is trained to output a command from the robot to steer towards its left. Table 5.1 shows the list of empirical training patterns based on Fig. 5.2.

During training and during normal operation, the input patterns fed to the neural network comprise the following components:

$$y_1^{\{1\}} = \text{Left obstacle distance from the robot} \qquad (5.1a)$$

$$y_2^{\{1\}} = \text{Front obstacle distance from the robot} \qquad (5.1b)$$

$$y_3^{\{1\}} = \text{Right obstacle distance from the robot} \qquad (5.1c)$$

$$y_4^{\{1\}} = \text{Target bearing of the robot} \qquad (5.1d)$$

These input values are distributed to the hidden neurons that generate outputs given by

$$y_2^{\{lay\}} = f\left(V_j^{\{lay\}}\right) \qquad (5.2)$$

Where

$$V_j^{\{lay\}} = \sum_i W_{ji}^{\{lay\}} . y_i^{\{lay-1\}} \qquad (5.3)$$

lay = layer number (2 or 3)

j = label for j^{th} neuron in hidden layer 'lay'

i = label for i^{th} neuron in hidden layer 'lay-1'

$W_{ji}^{\{lay\}}$ = weight of the connection from neuron i in layer 'lay-1' to neuron j in layer 'lay'.

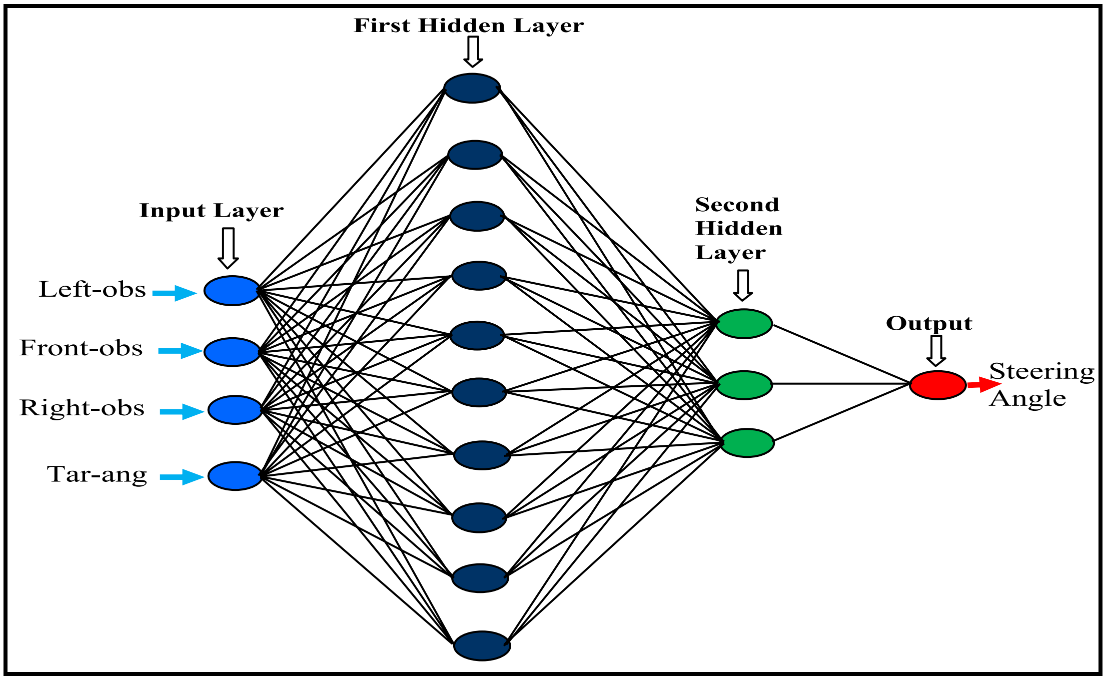


Figure 5.1. Four-layer neural network for robot navigation.

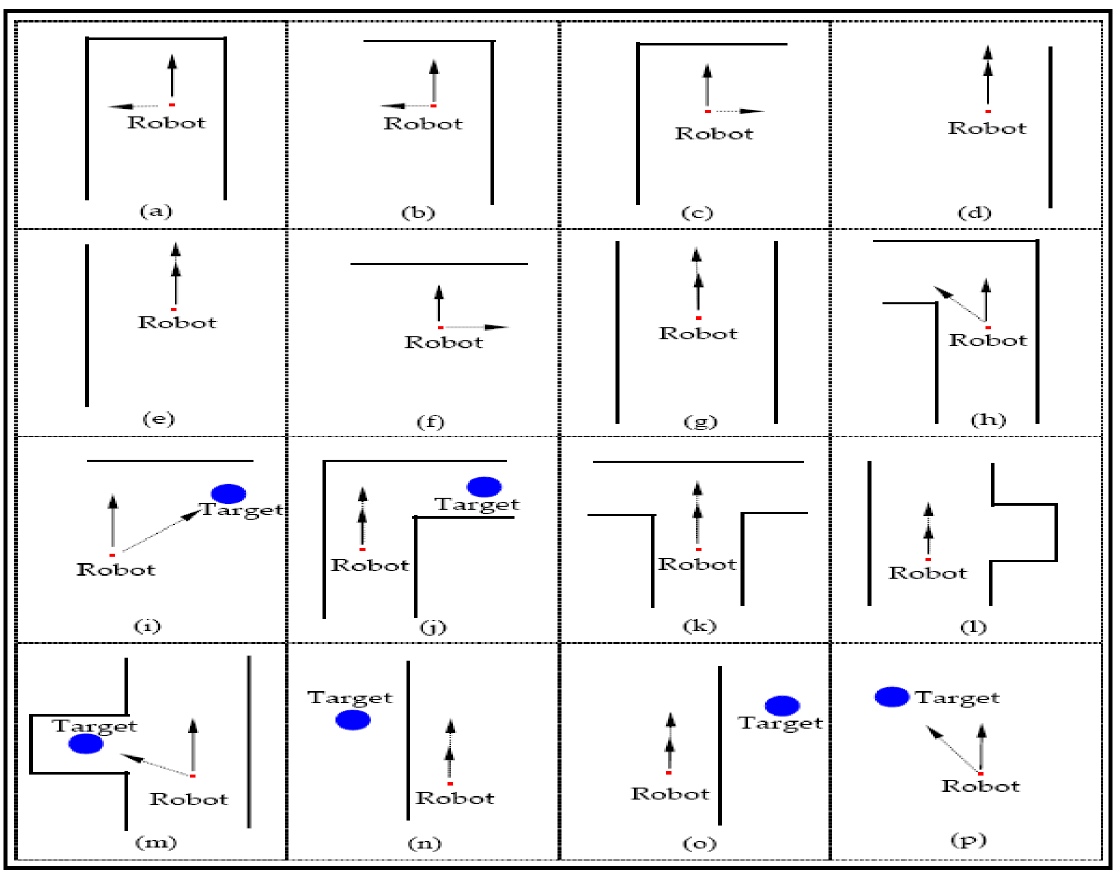


Figure 5.2. Example of training patterns.

Table 5.1. Some of the training pattern of neural controller

Position Figure 5.2	**Inputs of the network**				**Output**
	Front obstacle distance (cm)	**Right obstacle distance(cm)**	**Left obstacle distance(cm)**	**Target angle (degree)**	**Steering angle (degree)**
(a)	20	15	20	0	-180
(b)	20	15	100	0	-90
(c)	20	100	15	0	90
(d)	100	15	100	0	0
(e)	100	100	20	0	0
(f)	20	100	100	0	90
(g)	100	20	20	0	0
(h)	30	10	10	0	-20
(i)	30	100	100	35	30
(j)	30	15	10	45	10
(k)	30	10	10	0	5
(l)	100	30	15	0	0
(m)	100	15	30	-45	-40
(n)	100	100	10	-50	0
(o)	100	15	100	30	0
(p)	100	100	100	-20	-20

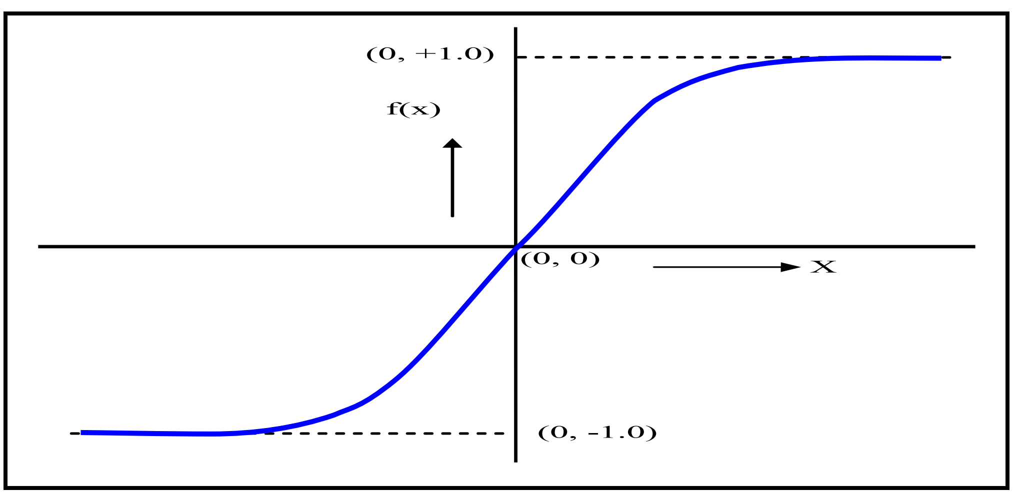


Figure 5.3. Hyperbolic tangent function used for activation function.

f(.) = activation function, chosen in this work as the hyperbolic tangent function shown in Fig. 5.3.

$$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{5.4}$$

During training, the network output θ_{actual} may differ from the desired output $\theta_{desired}$ as specified in the training pattern presented to the network. A measure of the performance of the network is the instantaneous sum-squared difference between $\theta_{desired}$ and θ_{actual} for the set of presented training patterns.

$$E_{rr} = \frac{1}{2} \sum_{\substack{\text{all training} \\ \text{patterns}}} (\theta_{desired} - \theta_{actual})^{2} \tag{5.5}$$

The error back propagation method is employed to train the network [215]. This method requires the computation of local error gradients in order to determine appropriate weight corrections to reduce Error. For the output layer, the error gradient $\delta^{\{4\}}$ is

$$\delta^{\{4\}} = f'\left(V_1^{\{4\}}\right)(\theta_{desired} - \theta_{actual}) \tag{5.6}$$

The local gradient for neurons in hidden layer {lay} is given by

$$\delta_j^{\{lay\}} = f'\left(V_j^{\{lay\}}\right)\left(\sum_k \delta_k^{\{lay+1\}} \; W_{kj}^{\{lay+1\}}\right) \tag{5.7}$$

The synaptic weights are updated according to the following expressions

$$W_{ij}(t+1) = W_{ij}(t) + \Delta W_{ij}(t+1) \tag{5.8}$$

And

$$\Delta W_{ij}(t+1) = \alpha \Delta W_{ij}(t) + \Delta\eta \delta_j^{\{lay\}} y_i^{\{lay-1\}} \tag{5.9}$$

Where

α = momentum coefficient (chosen empirically as 0.2 in this work)

η = learning rate (chosen empirically as 0.35 in this work)

t = iteration number, each iteration consisting of the presentation of a training pattern and correction of the weights.

Table 5.2. Reactive behaviours adopted by mobile robot during navigation

Types of Behaviour	**Description of the behaviours**	**Implementations**
Obstacle avoidance	(i)Mobile robot detects (by sensory information) any obstacle in front, left or right side. This behaviour required to avoid collision with obstacle (Fig. 5.4). (ii)When the acquired information from the sensors shows the presence of obstacles to the front, left and right side of the robot. The robot reverses its movement (Fig. 5.4).	The robot reduces the speed and set the steering angle accordingly. The robot stopped and takes counter clockwise rotation both left and right wheel in same speed (i.e. reverse direction).
Target seeking	When the acquired information from the sensors shows that there are no obstacles around the robot, its main reactive behaviour is to seek the target. This behaviour requires to locate the target (Fig. 5.4).	The robot mainly adjusts its motion direction and quickly moves towards the target.
Wall following	Mobile robot detects an obstacle in the front while it is moving towards target and also having wall to the left or right side. The robot has to follow the wall to reach the target (Fig. 5.5).	The robot adjust the speed and set the heading angle 90° with wall so that it align with wall and moves along the wall. The robot automatically makes turns to align itself along the wall and move parallels with the wall to reach the target.

The final output from the neural network is

$$\theta_{\mathrm{actual}} = f(V_1^4) \tag{5.10}$$

Where

$$V_1^4 = \sum_i W_{1i}^{\{4\}} y_i^{\{3\}} \tag{5.11}$$

It should be noted learning can take place continuously even during normal target seeking behaviour. This enables the controller to adopt the changes in the robot's path while moving towards target. Mainly three behaviours (obstacle avoidance, wall following and target seeking) are required to train and to design an intelligent controller for mobile robot being used to navigate in a cluttered environment. Table 5.2 depicts the used behaviour being trained by network.

5.3 Simulation Results and Discussions

Existing approaches for learning to control a mobile robot rely on supervised methods, where correct behaviour is explicitly given. The simulation results present the effectiveness of novel approach that evolves neural network controller. The series of simulations test have been conducted with the ROBNAV software (Appendix–A). To demonstrate the effectiveness and the robustness of the proposed method, simulation results on mobile robot navigation in various environments are exhibited.

For visual guidance of behaviour, in navigation the perception of motion plays a prominent role. An important part of robot behaviour is avoidance of obstacles. Examples of static obstacles include walls, poles, fences, trees etc. as well as other moving obstacle like vehicles, people, animals etc. Encountering such objects can cause avoidance behaviour, which consists of any combination of slowing down, turning, and stopping (Fig. 5.4). The wall following behaviour is required to move from one room to another room. The wall following behaviour mode will be adopted when the mobile robot detects an obstacle in the front while it is moving towards target, the mobile robot may turn left or right because presence of obstacle in the front. In this case, the robot tries to maintain perpendicular to the wall. The simulation result of wall following behaviour is shown in Fig. 5.5.

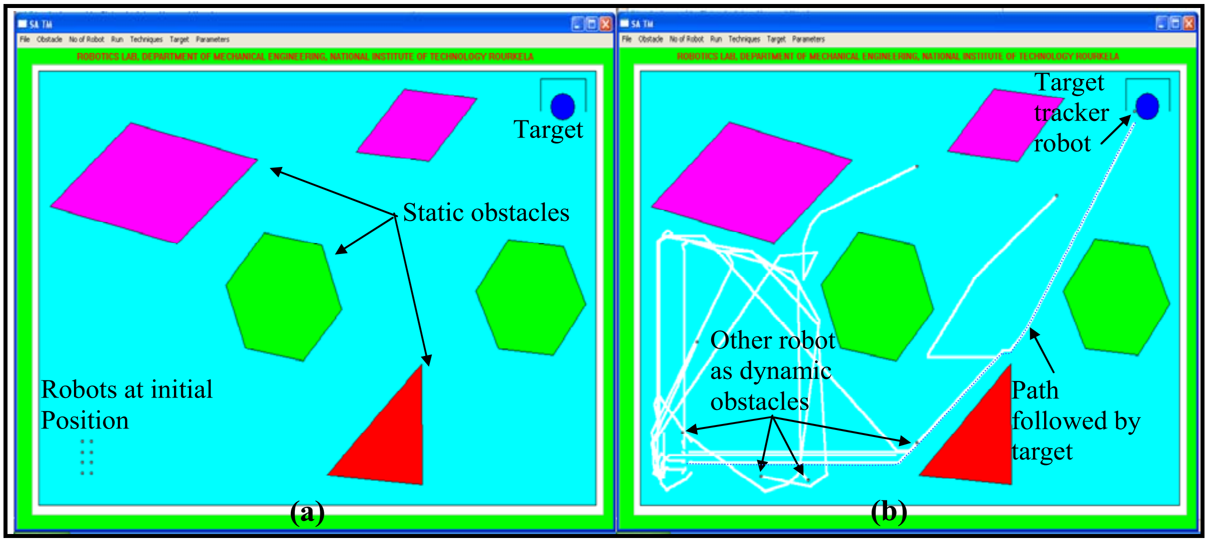


Figure 5.4. Static as well as dynamic obstacle avoidance behaviour (a) At initial position before simulation (b) Navigational path during simulation.

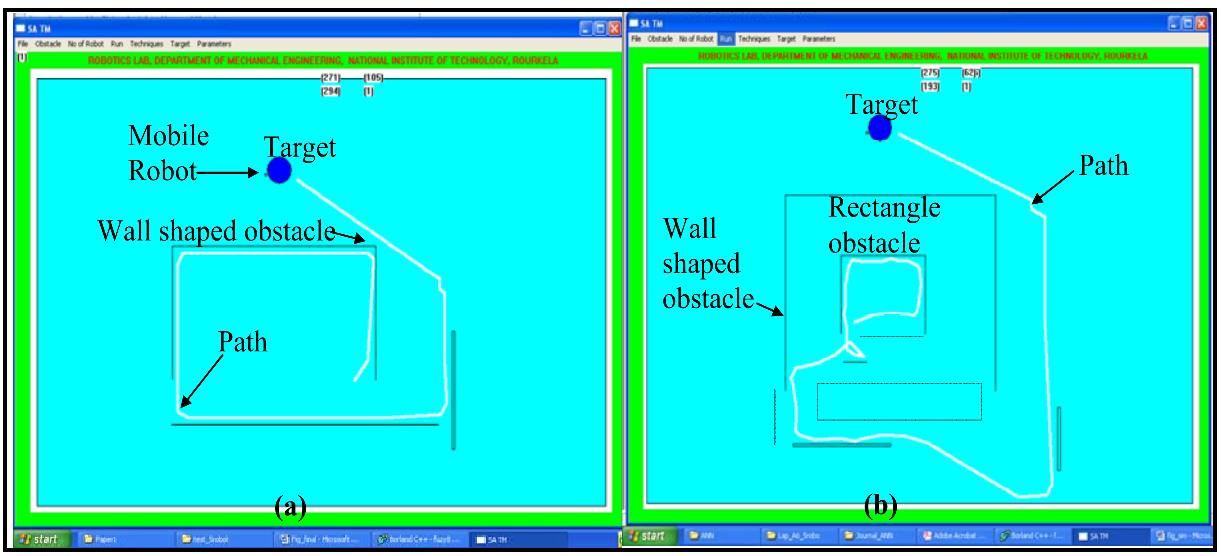


Figure 5.5. Robot with wall following behaviour (b) Robot escaping from dead end obstacles.

Target searching algorithms assume that the goal state is fixed and does not change during navigation of mobile robot. For example, in the problem of moving from the current location to a desired goal location along a network of paths, it is assumed that the target location is fixed and does not change during the navigation. Neural controller mainly adjusts robots motion direction and quickly moves it towards the target if there are no obstacles around the robot as shown in Fig. 5.4. In the proposed control strategy, reactive behaviours are formulated and trained by neural network.

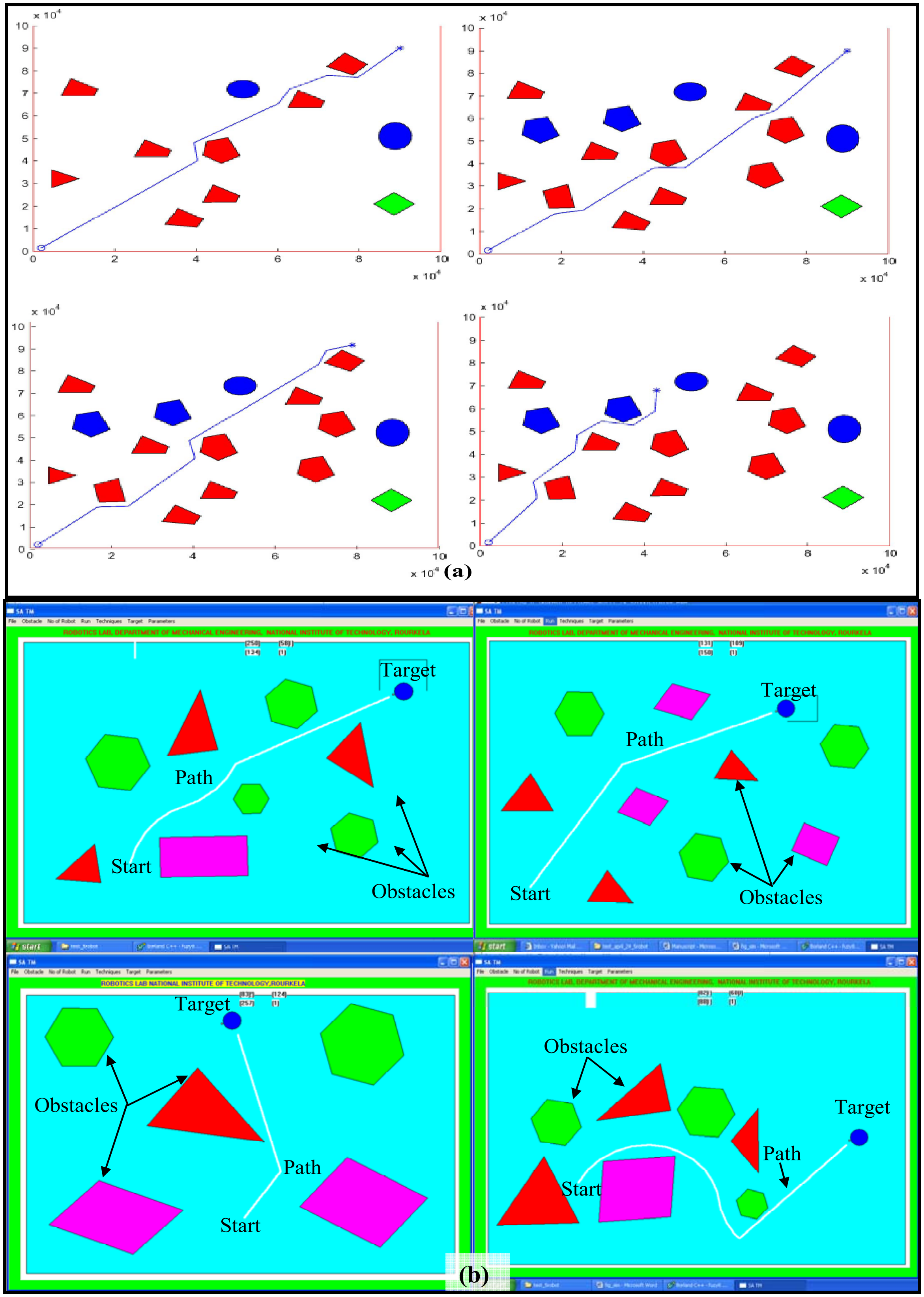


Figure 5.6. (a) Navigation of a mobile robot in unknown environment by Ray et al. [216] (b) Navigation of a mobile robot in unknown environment using a developed controller.

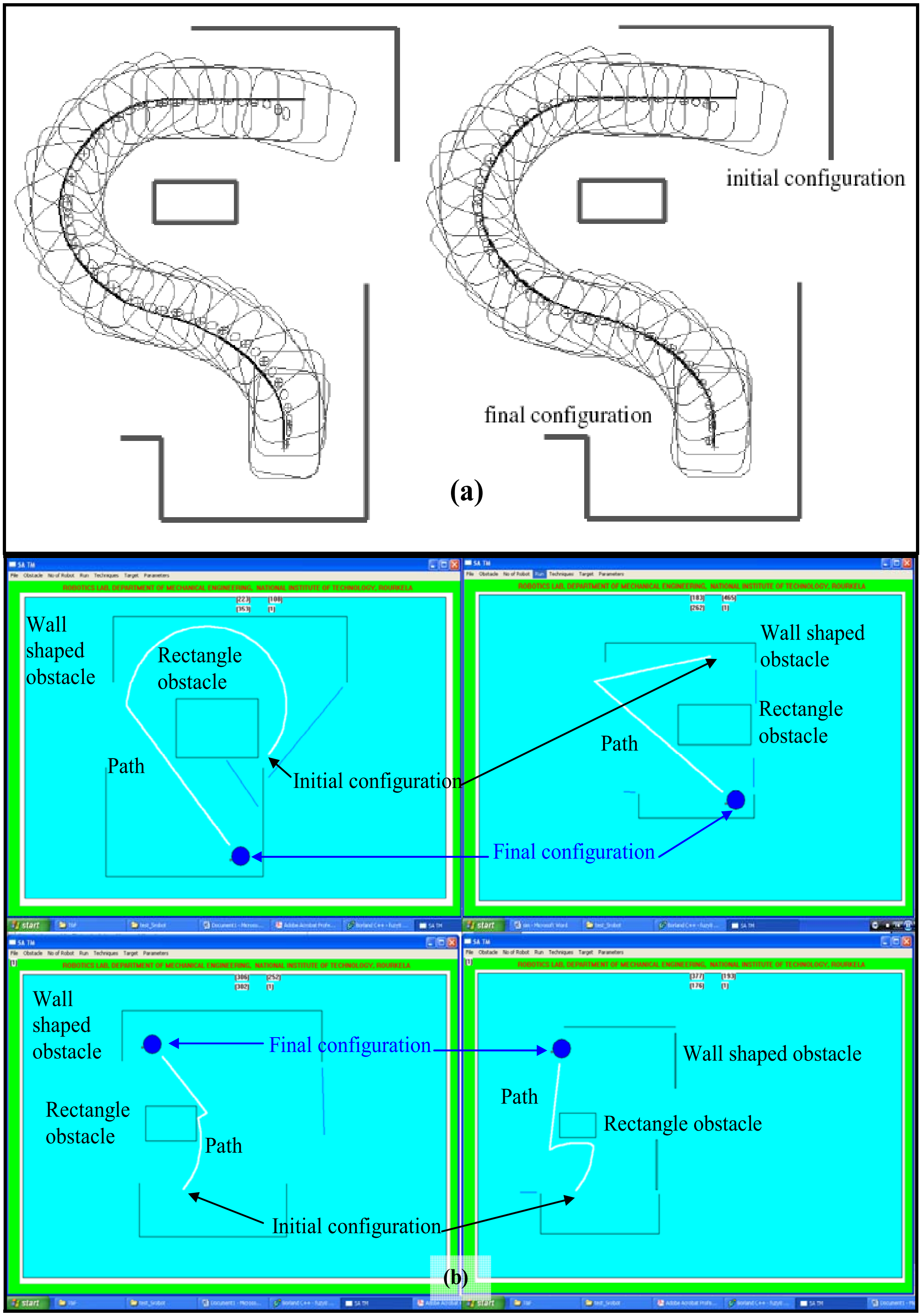


Figure 5.7. (a) Experimental result of planned path by Hamel et al. [194] (b) Navigation of mobile robot using developed controller.

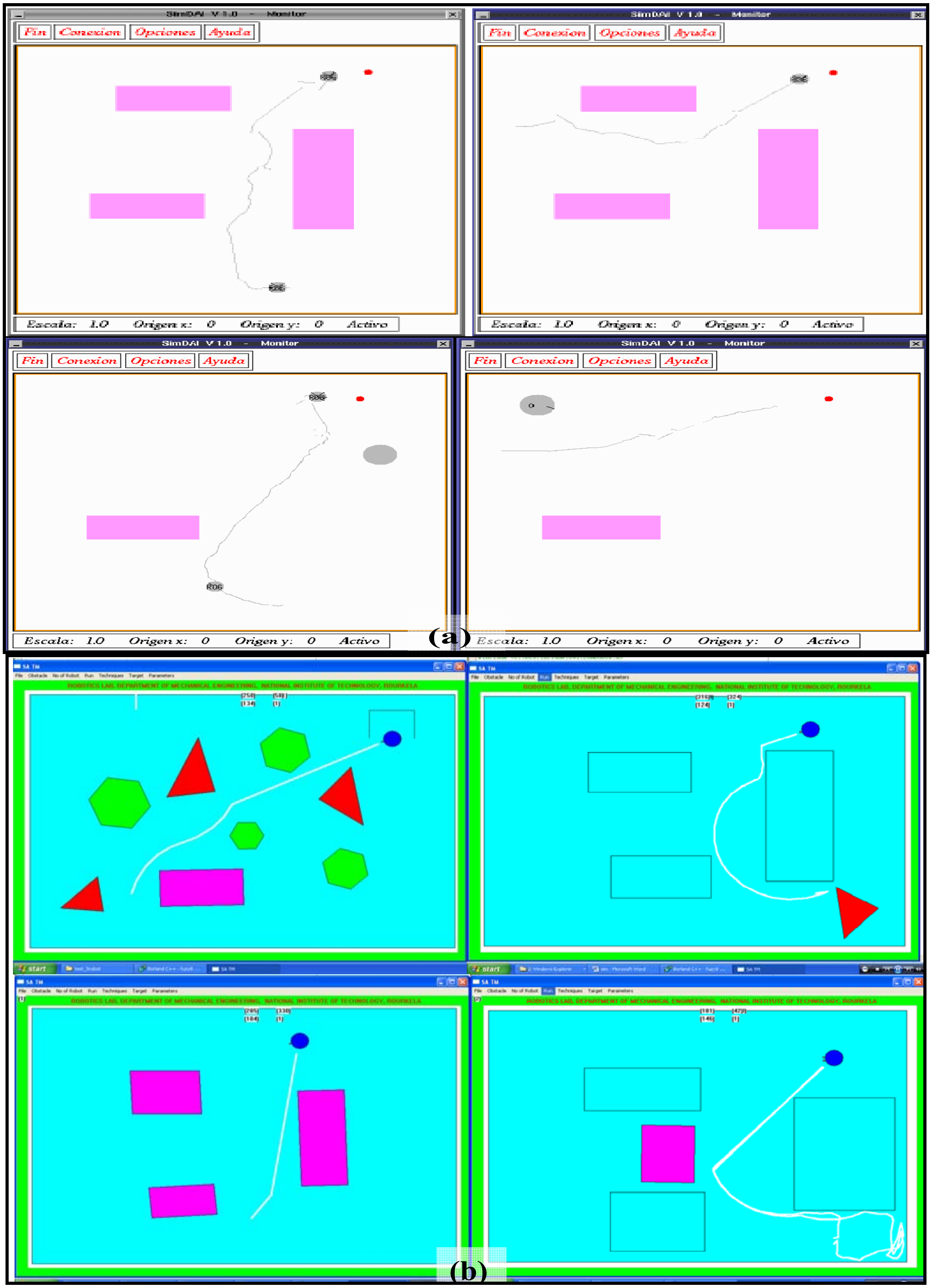


Figure 5.8. (a) Static and dynamic experimental result by Sanchis et al. [214] (b) Static and dynamic simulation result by developed neural controller.

In order to exhibit the effectiveness of the proposed neural controller of mobile robot, the results obtained by Ray et al. [216] for navigation of a mobile robot in an unknown environment (Fig. 5.6(a)) are compared with obtained the results from the current developed controller (Fig. 5.6(b)). They show a very good agreement. The results obtained using feedback control law by Hamel et al. [194] have been compared with the results obtained from proposed neural controller of mobile robot (Fig. 5.7). In addition, a comparison has been done between the static and dynamic result using classifier systems described by Sanchis et al. [214] and results obtained from the current developed controller (Fig. 5.8). The comparisons show a good agreement.

5.4 Experimental results

The navigation method has been tested in a series of experiments to exhibit its effectiveness. All experimental result carried out using C++ executable code loaded on Khepera-III (Appendix-C.2) mobile robot. The position of wheels and sensors of Khepera-III mobile robot has been depicted in Fig. 5.9. The assumptions about the mechanical structure and the motion of the mobile robot moves on a plane surface and wheels are pure rolling.

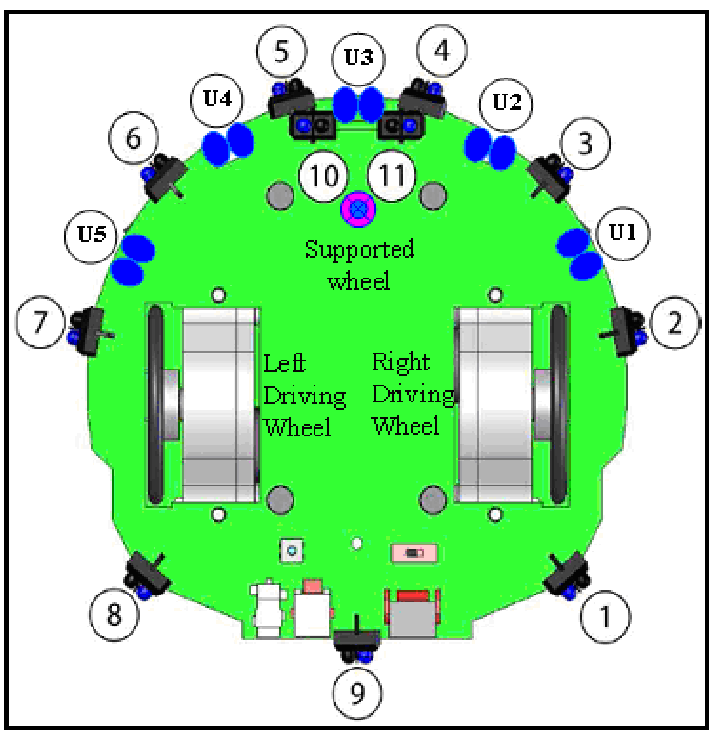


Figure 5.9. The chassis of the KHEPERA-III robot.

Table 5.3 Time taken by robots in simulation and experiment to reach targets

S. No.	Average of 9 experiments in each environment	Path length (in pixel)	Time during simulation(sec.)	Time during experiment(sec.)
01.	For 1st environment scenario Fig. 5.10-i and Fig.5.11(a)	221	23	26
02.	For 2nd environment scenario Fig. 5.10-ii and Fig.5.11(b)	206	22	25
03	For 3rd environment scenario Fig. 5.10-iii and Fig.5.11(c)	175	18	21
04	For 4th environment scenario Fig. 5.10-iv and Fig.5.11(d)	234	25	27

From the neural controller (inputs: left, front, right obstacle distances and heading angle) after learning and training, robots get the left and right wheel velocities which subsequently give the new steering angles. During experiment, it has been found that the experimental path lengths and time taken are more than the simulation path lengths and time taken. This is due to presence of various errors (e.g. signal transmission error in data-cable, obstacle/ target tracking error, presence of friction in rotating elements, slippage between floor and wheels, friction between supported point and floor etc.). Table 5.3 shows the times taken by the robots in simulations and in the experimental tests during finding the targets.

The experiment has been conducted in the laboratory for different environmental scenarios. The figures given are the averages of three experiments on each environmental scenario conducted in the laboratory. All mention above robotics behaviours are verified in simulation and experimental mode (Fig. 5.10 and Fig.5.11). The fuzzy logic controller proposed by Pradhan et al. [213] has been examined and compared with the proposed neural controller in a similar navigational environment. It has been found that the neural controller gives a more optimised path than the fuzzy controller (the total path length using a fuzzy controller by Pradhan et al. [213] is 13.7m and the time taken is 14.67 s to reach the target, whereas the total path length using a proposed neural controller is 12.0m and the time taken is 12.84 s). In addition, a neural controller requires less computing time and computing memory than a fuzzy controller.

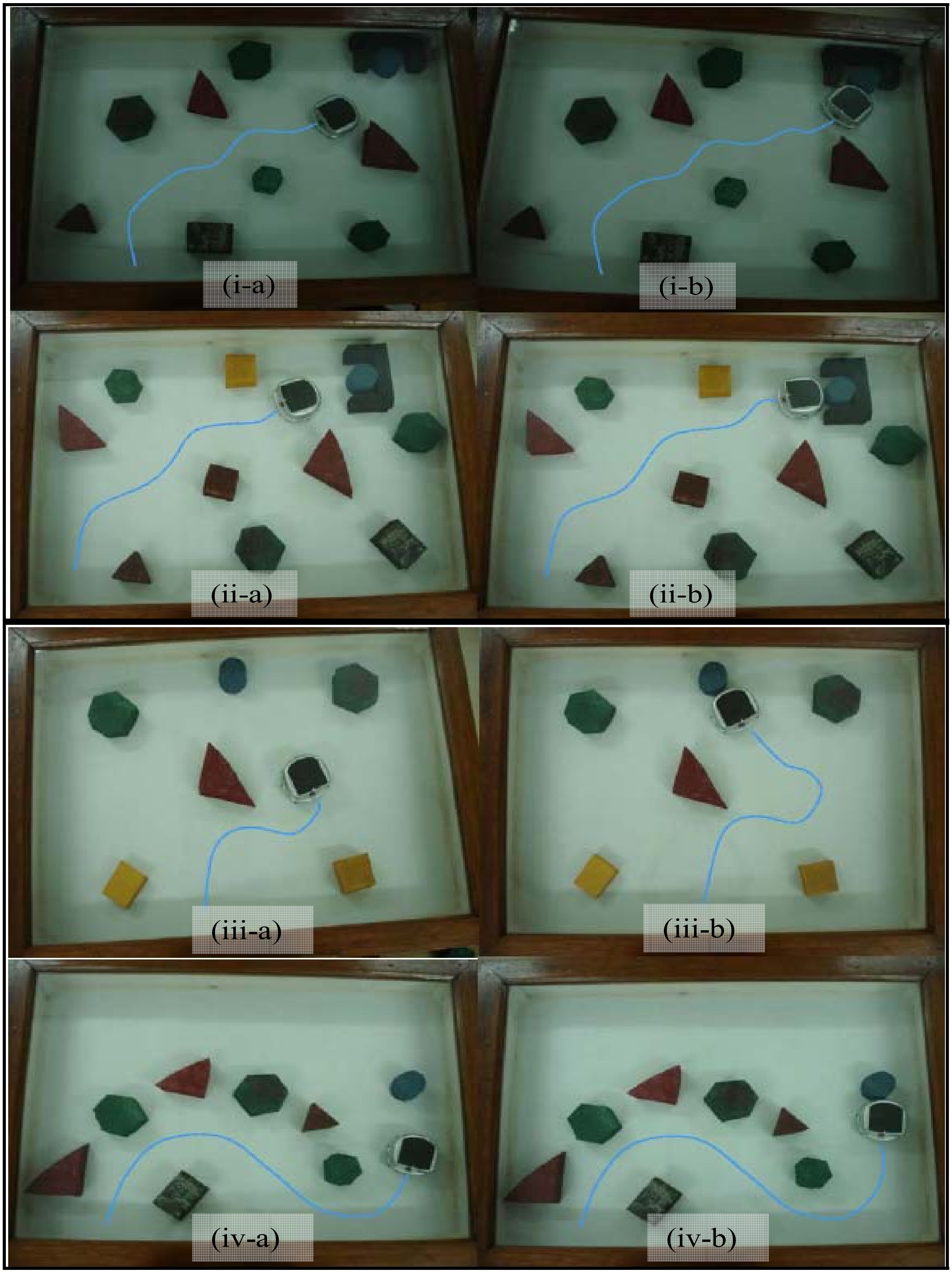


Figure 5.10. Experimental results during target seeking by the mobile robot in various environments

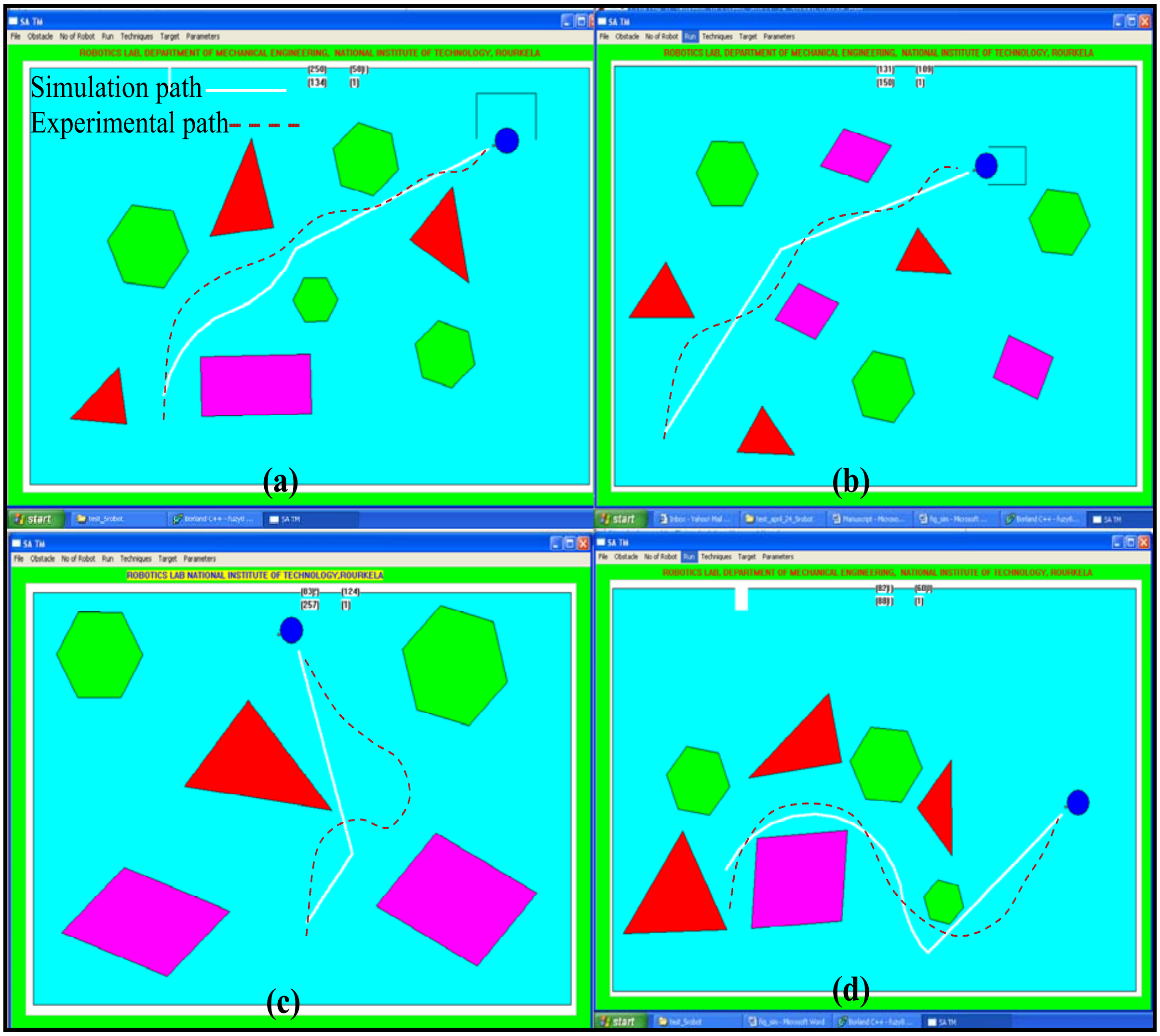


Figure 5.11. Comparison of experimental results with simulation results.

It has been observed that the robot controlled through neural control has better performance than the fuzzy controller in terms of positioning accuracy and collision avoidance and it provides optimise path to reach the goal.

Table 5.4. Simulation results comparison between the fuzzy controllers developed by Pradhan et al. [213] and the current developed neural controller

S. No.	Navigation with different method	Fuzzy controller	Neural controller	Percentage of deviation
01.	Length of path (in meter)	13.8	12.2	11.58 %
02.	Time taken (seconds)	14.67	12.97	11.59 %

5.5 Summary

The conclusion drawn based on the theoretical; simulations and experimental analysis are depicted below.

Both in simulation and experimental modes the developed controller worked efficiently. The simulation results are also compared with the results obtained from the other investigations and they show a very good agreement. Back-propagation neural network is used to design the controller. The developed neural controller has got the following salient feature:

1. Mobile robots are able to avoid any static and dynamic obstacles on their path. In dynamic environment, the proposed neural controller can be efficiently applied.
2. During navigation using the sensors information robots are able to map the surrounding.
3. On comparison with three various approaches (i.e. feedback control law, classifier systems and fuzzy controller) it is found that the developed controller is simple but efficient for navigation of mobile robot in dynamic environment.
4. Training patterns of each network can be generated by simulation rather than by experiment, saving considerable time and effort.
5. behaviours such as obstacle avoidance, wall following, and target seeking are integrated in the current controller to obtain an efficient navigational controller.

Some features of the intelligent controller cannot be added by using a single technique like fuzzy logic or neural network technique. Certainly, these two fields can be integrated into a new emerging technology called adaptive neuro-fuzzy system, which combines the benefits of each field (i.e. perception, cognition, and motion control). Next chapter, describes a hybrid controller for more efficient navigation of the mobile robots.

❖ Publications

1. "Real time navigational control of mobile robots using artificial neural network" *Journal of Mechanical Engineering Science part C*, I MechE, 223(7), 2009, 1713-1725.
2. "Path optimisation of mobile robot using artificial neural network (ANN) controller", *International Journal of System Science*, Taylor & Francis, 2009, (Accepted).
3. "Intelligent Neuro-controller for Navigation of Mobile Robot" *International conference on ICAC3'09*, January 23–24, 2009, Mumbai, India.

6 Adaptive Neuro-Fuzzy Controller for Navigation of Mobile Robots

This chapter provides about navigation control of multiple mobile robot using adaptive neuro-fuzzy inference system (ANFIS) in cluttered environment. In the ANFIS controller after the input layer there is a fuzzy layer and rest of the layers are neural layers. The adaptive neuro-fuzzy hybrid system combines the advantages of fuzzy logic system, which deal with explicit knowledge that can be explained and understood, and neural networks, which deal with implicit knowledge, which can be acquired by learning. The merger of neural networks and fuzzy logic led to the creation of neuro-fuzzy controllers which are currently one of the most popular research fields. The inputs to fuzzy logic layer are front obstacle distance, left obstacle distance, right obstacle distance and target steering. A learning algorithm based on neural network technique has been developed to tune the parameters of fuzzy membership functions, which smooth the trajectory generated by the fuzzy logic system. Using the developed ANFIS controller, the mobile robots are able to avoid static and dynamic obstacles, and reach the target successfully in cluttered environments. The experimental results agree well with the simulation results, proves the authenticity of the theory developed.

6.1 Introduction

Researchers strive to develop new concepts and strategies to improve existing ones in the area related to mobile robot navigation. To do this, criteria for optimal performance and ways to optimise design, structure and control of robots must be developed and implemented. The current robot navigation systems require controllers able to solve complex problems under very uncertain and dynamic environmental situations. Presently, the ANFIS approach is becoming one of the major areas of interest because it gets the benefits of neural networks as well as of fuzzy logic systems and it removes the individual disadvantages by combining them on the common features. The artificial neural network has injected a new driving force into the fuzzy literature.

Fuzzy systems are able to treat uncertain and imprecise information, they make, use of knowledge in the form of linguistic rules. Their drawbacks are caused mainly by the difficulty of designing accurate membership functions and lack of a systematic procedure for the transformation of expert knowledge into the rule base. Neural networks have the ability to learn but with some neural networks, knowledge representation and extraction are difficult [152]. An algorithm for mapping using sparse constraint graphs is descried by Thrun et al. [217] which obtains the map and the robot path. Their methodology optimises the simultaneous localization and mapping problems. A methodology used to describe the interaction between perception and action, can be adapted to yield a mobile robot system that is highly sensitive to the currently perceived world [211]. Reactive control is an approach to robotics that eliminates the use of intervening representation and reasoning during the execution of a robot's mission.

In this chapter, ANFIS approach has been proposed for real time navigation of mobile robot. In the present work, a time-optimal and collision-free path has been developed for navigation of mobile robot in unknown and cluttered environments. To achieve optimised path and time, this chapter proposes a path planning approach based on ANFIS which emulates the human driving behaviour. Fuzzy logic has been used for behaviour design such as obstacle avoidance, wall following and target seeking which negotiates uncertain and imprecise information; they make use of knowledge in the form of linguistic rules. The developed ANFIS is based on a fuzzy system, which is trained by a learning algorithm derived from neural network theory. Learning allows autonomous robots to acquire knowledge by interacting with the environment and subsequently adapting their behaviour and solve the problem of insufficient knowledge for designing the controller rule-base. The ANFIS learns and generates the required knowledge for achieving desired goals from the mobile robot behaviour and its environment. Numerical examples are presented to demonstrate the validity of the approach. The simulation results are compared with the results from other methods [90, 98, 213, 218]. Experimental results are verified with simulation results to demonstrate the effectiveness of the proposed methodology.

This chapter is organised into five sections following the introduction; the entire ANFIS architecture has been discussed in section 6.2. The simulation results are presented in section 6.3 and experimental results are analyzed in section 6.4. Finally, the summary is given in section 6.5.

6.2 Analysis of ANFIS

The adaptive neuro fuzzy inference system (ANFIS) is an integrated system of artificial neural network (ANN) and fuzzy inference system (FIS). The ANFIS analysed here is a first order Takagi Sugeno Fuzzy Model [150, 156]. In the current analysis there are four inputs Front obstacle distance (x_1), Right obstacle distance (x_2), Left obstacle distance(x_3) and Target angle(x_4) and the output is Steering angle. The if-then rules for the ANFIS architecture are defined [150] as follows;

Rule: **IF** x_1 is A_j, x_2 is B_k, x_3 is C_m and x_4 is D_n **THEN** $f_i = p_i x_1 + r_i x_2 + s_i x_3 + t_i x_4$

Where;

$$f_i = p_i x_1 + r_i x_2 + s_i x_3 + t_i x_4 + u_i \text{ ; for steering angle} \tag{6.1}$$

$j = 1$ to q_1; $k = 1$ to q_2; $m = 1$ to q_3; $n = 1$ to q_4 and $i = 1$ to $q_1 . q_2 . q_3 . q_4$

A, B, C and D are the fuzzy membership sets defined for the input variables x_1, x_2, x_3 and x_4. q_1, q_2, q_3 and q_4, are the number of member ship functions for the fuzzy systems of the inputs x_1, x_2, x_3 and x_4 respectively. f_i is the linear consequent functions defined in terms of the inputs (x_1, x_2, x_3 and x_4) . p_i, r_i, s_i , t_i and u_i are the consequent parameters of the ANFIS fuzzy model. In the ANFIS model, nodes of the same layer have similar functions. The output signals from the nodes of the previous layer are the input signals for the current layer. The output obtained with the help of the node function will be the input signals for the subsequent layer (Fig. 6.1).

Layer 1: The input layer receives signal from arrays of sensors x_1, x_2, x_3, x_4, which defines the static as well as moving obstacles, and target poisons from the target tracker robot. The target position measured according to the target coordinates. The coordinates are given to the robots during navigation. The robot measures its global position according to its wheel movements during navigation.

Layer 2: Every node in this layer is an adaptive node (square node) with a particular fuzzy membership function (node function) specifying the degrees to which the inputs satisfy the quantifier. For four inputs the outputs from nodes are given as follows;

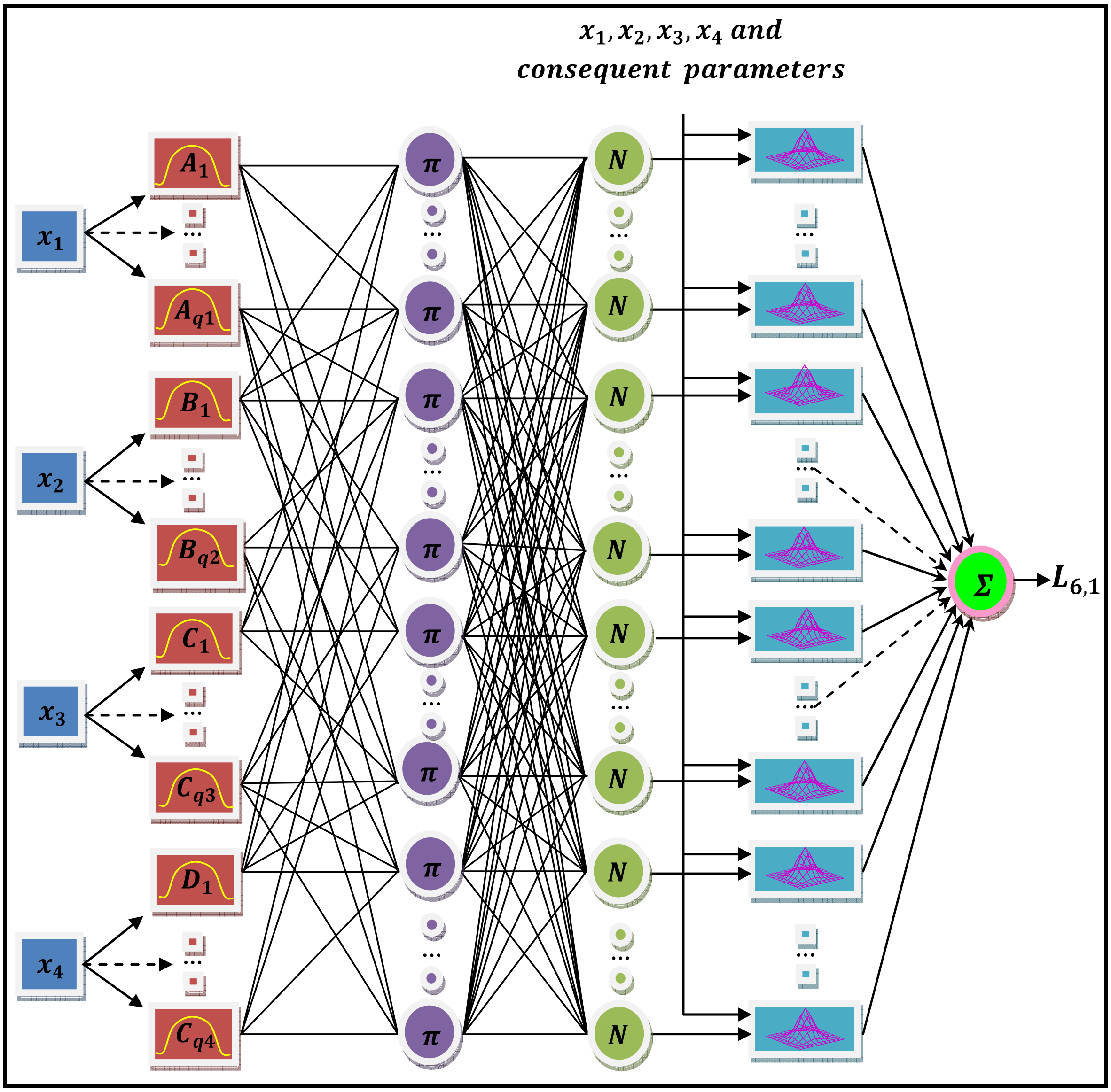


Figure 6.1. Six-layers ANFIS architecture for robot navigation.

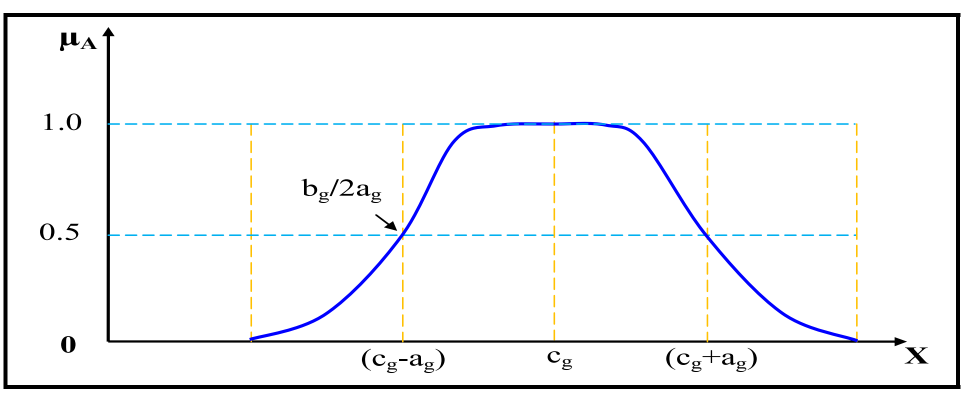


Figure 6.2. Bell shaped membership function used for fuzzy inference system.

$L_{2,g} = \mu_{Ag}(x)$ for $g = 1, \dots, q_1$ (For input x1)

$L_{2,g} = \mu_{Bg}(x)$ for $g = q_1 + 1, \dots, q_1 + q_2$ (For input x2)

$L_{2,g} = \mu_{Cg}(x)$ for $g = q_1 + q_2 + 1, \dots, q_1 + q_2 + q_3$ (For input x3)

$L_{2,g} = \mu_{Dg}(x)$for $g = q_1 + q_2 + q_3 + 1, \dots, q_1 + q_2 + q_3 + q_4$ (For input x4)

Here the membership function for A, B, C and D considered are the bell shaped function and are defined as follows;

$$\mu_{Ag}(x) = \frac{1}{1+\left\{\left(\frac{x-c_g}{a_g}\right)^2\right\}^{b_g}} \; ; \; g = "1" \text{ to } "q_1" \tag{6.2}$$

$$\mu_{Bg}(x) = \frac{1}{1+\left\{\left(\frac{x-c_g}{a_g}\right)^2\right\}^{b_g}} \; ; \; g = "q_1 + 1" \text{ to } "q_1 + q_2" \tag{6.3}$$

$$\mu_{Cg}(x) = \frac{1}{1+\left\{\left(\frac{x-c_g}{a_g}\right)^2\right\}^{b_g}} \; ; \; g = "q_1 + q_2 + 1" \text{ to } "q_1 + q_2 + q_3" \tag{6.4}$$

$$\mu_{Dg}(x) = \frac{1}{1+\left\{\left(\frac{x-c_g}{a_g}\right)^2\right\}^{b_g}} \; ; \; g = "q_1 + q_2 + q_3 + 1" \text{ to } "q_1 + q_2 + q_3 + q_4" \tag{6.5}$$

Where a_g b_g and c_g are the parameters for the fuzzy membership function. The ball-shaped function (Fig. 6.2) changes its pattern as per the change of the parameters. This change will give the various contour of bell shaped function as needed in accord with the data set for the problem considered.

Layer 3: Every node in this layer is a fixed node (circular) labeled as "π". The output denoted by $L_{2,i}$ the output is the product of all incoming signal.

$$L_{3,i} = W_i = \mu_{Ag}(x), \mu_{Bg}(x), \mu_{Cg}(x), \mu_{Dg}(x); \tag{6.6}$$

for $i = 1, \dots, q_1, q_2, q_3, q_4$ and $g = 1, \dots \dots, q_1 + q_2 + q_3 + q_4$

The output of each node of the second layer represents the firing strength (degree of fulfillment) of the associated rule. The T-norm operator algebraic product $\{T_{ap}(a,b) = ab\}$, has been used to obtain the firing strength (W_i).

Layer 4: Every node in this layer is a fixed node (circular) labeled as "N". The output of the i^th node is calculated by taking the ratio of firing strength of i^th rule (W_i) to the sum of all rules' firing strength.

$$L_{4,i} = \overline{W_i} = \frac{W_i}{\sum_{r-1}^{r=q_1 \cdot q_2 \cdot q_3 \cdot q_4} W_r} \tag{6.7}$$

This output gives a normalized firing strength.

Layer 5: Every node in this layer is an adaptive node (square node) with a node function.

$$L_{5,i} = \overline{W_i}\, f_i = \overline{W_i}\,(p_i x_1 + r_i x_2 + s_i x_3 + t_i x_4 + u_i) \tag{6.8}$$

Where $\overline{W_i}$ is a normalized firing strength form (output) from layer 3 and $\{p_i,\ r_i,\ s_i,\ t_i,\ u_i\}$ is the parameter set for steering angle. Parameters in this layer are referred to as consequent parameters.

Layer 6: The single node in this layer is a fixed node (circular) labeled as "Σ", which computes the overall output as the summation of all incoming signals.

$$L_{6,1} = \sum_{i-0}^{i=q_1 \cdot q_2 \cdot q_3 \cdot q_4} \overline{W_i}\, f_i = \frac{\sum_{i-0}^{i=q_1 \cdot q_2 \cdot q_3 \cdot q_4} W_i f_i}{\sum_{i-0}^{i=q_1 \cdot q_2 \cdot q_3 \cdot q_4} W_i} \tag{6.9}$$

In the current developed ANFIS structure there are six dimensional space partitions and has "$q_1 \times q_2 \times q_3 \times q_4$" regions. Each region is governed by a fuzzy if then rule. The first layer is the input layer. The second layer (consists of premise or antecedent parameters) of the ANFIS and is dedicated to fuzzy sub space. The third and fourth layer is fixed node (circular) labeled as π and N. The parameters of the fifth layer are referred as consequent parameters and are used to optimise the network. The first order Takagi-Sugeno model is used for difuzzyfication in fifth and sixth layer. During the forward pass of the hybrid learning algorithm node outputs go forward till layer five and the consequent parameters are identified by least square method. In the backward pass, error signals propagate backwards and the premise parameters are updated by a gradient descent method.

6.3 Simulation Results

The simulations results are obtained by using ROBNAV software (Appendix-A). To demonstrate the effectiveness and the robustness of the proposed method, simulation results on mobile robot navigation in various environments are exhibited.

The obstacle avoidance behaviour is activated when the readings from any sensors are less than the minimum threshold values (50 mm). This is how the robot determines if an object is close enough for a collision. When an object is detected too close to the robot, it avoids a collision by moving away from it in the opposite direction. Collision avoidance has the highest priority and therefore, it can override other behaviours, in this case, its main reactive behaviour is decelerating for static as well as dynamic obstacle avoidance as shown in Fig. 6.3 (a). When the acquired information from the sensors shows that there are no obstacles around robot, its main reactive behaviour is target steer. ANFIS mainly adjusts robots motion direction and quickly moves it towards the target if there are no obstacles around the robot as shown in Fig. 6.3 (b). In the proposed control strategy, reactive behaviours are formulated and trained by ANFIS.

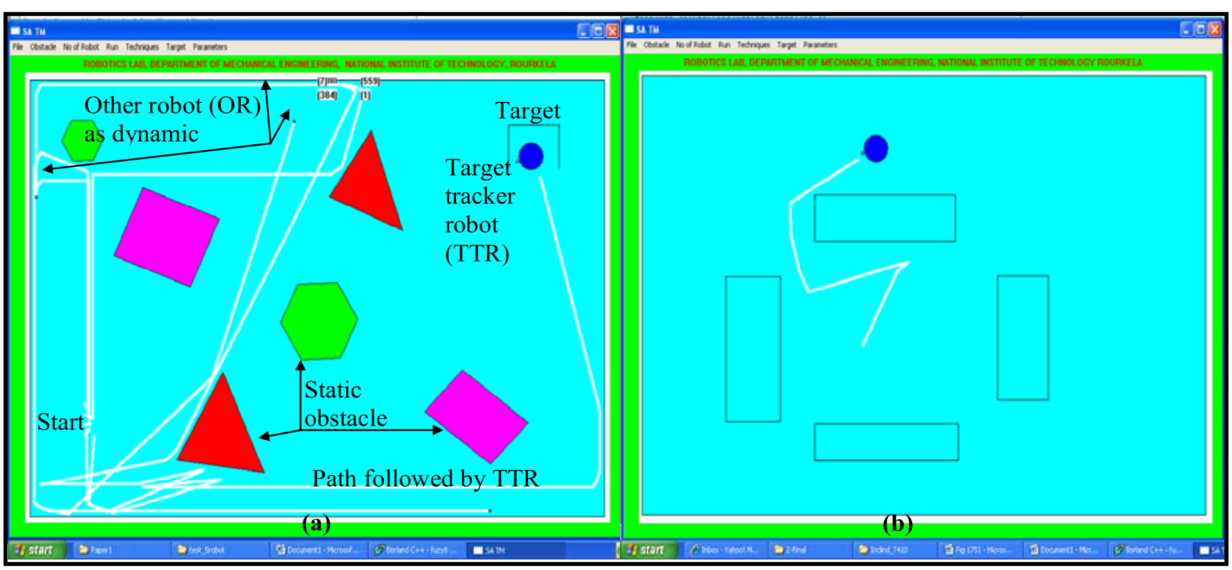


Figure 6.3. (a) Static as well as dynamic obstacle avoidance behaviour (b) Target seeking behaviour of mobile robot.

Another special condition appears as the mobile robot detects an obstacle in the front while the target tracking control mode is on operation. In this case, the fixed wall following behaviour should be performed first, that is, the mobile robot must rotate clockwise or counterclockwise such that it can align and move along the wall. When the robot is moving to a specified target through a narrow channel, dead end or escaping from a U shaped obstacle, in such a situation the robot should keep on heading towards the goal position. But when it moves towards the goal position, the robot also comes across the obstacles. Any obstacle-avoidance behaviour except wall following behaviour would make the robot divert from its goal position. The navigation path of mobile robot by purposed ANFIS methodology and escaping from dead end has been shown in Fig 6.4 (a) and Fig. 6.4 (b).

The results obtained from the proposed ANFIS approach for real time navigation of mobile robot during vehicle controlled motion with a cluttered obstacle environment from two different goal and starting points have been compared with the result from Abdessemed et al. [90] during vehicle controlled motion with a cluttered obstacle environment from two different starting points (shown in Fig. 6.5). Apart from comparison between fuzzy and neural technique a comparison has also been made between the current developed controller and the potential field method proposed by Arkin [211] during navigation of robot, shown Fig 6.6.

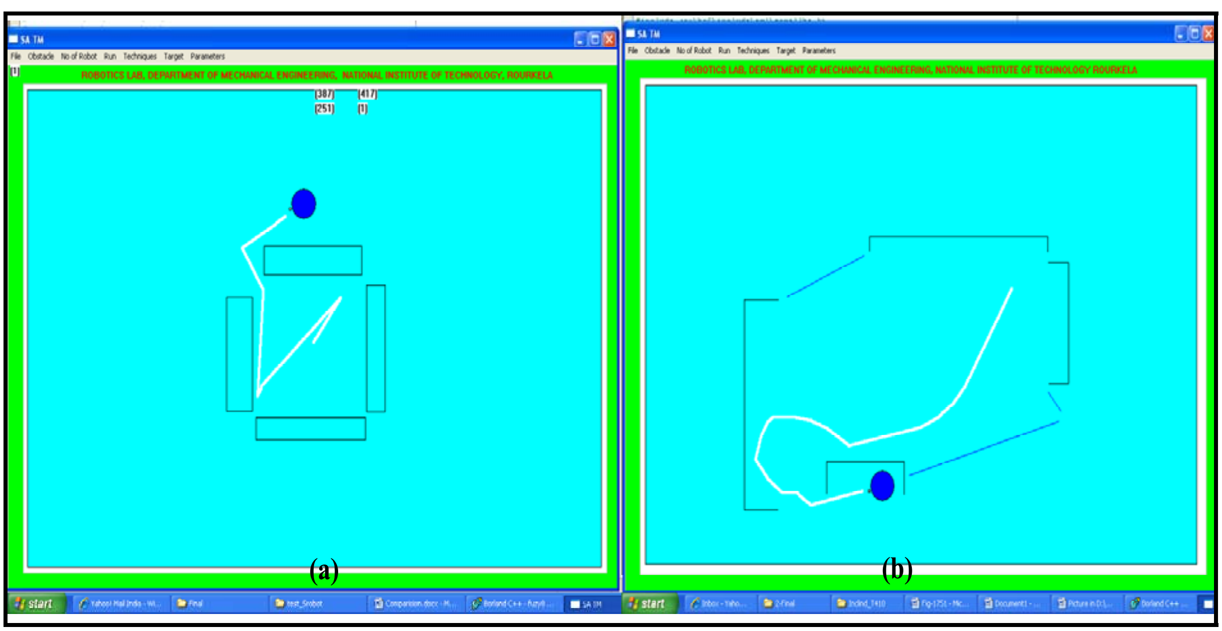


Figure 6.4. (a) Navigation path of mobile robot by purposed ANFIS (b) Escaping from dead end by purposed ANFIS methodology.

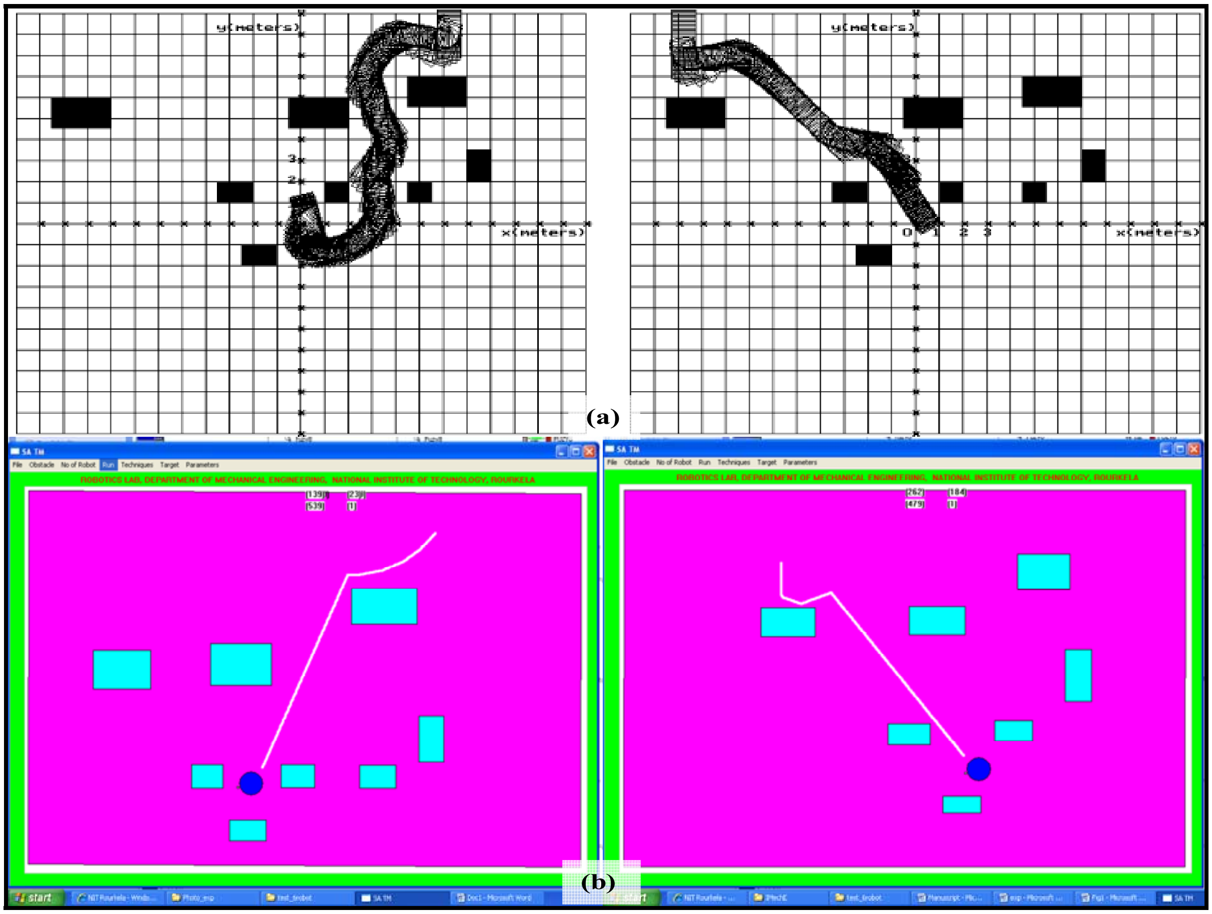


Figure 6.5. (a) Results of Abdessemed et al. [90] during vehicle controlled motion with a cluttered obstacle environment from two different starting points. (b) Results of proposed ANFIS approach during vehicle controlled motion with a cluttered obstacle environment from two different goal and starting points.

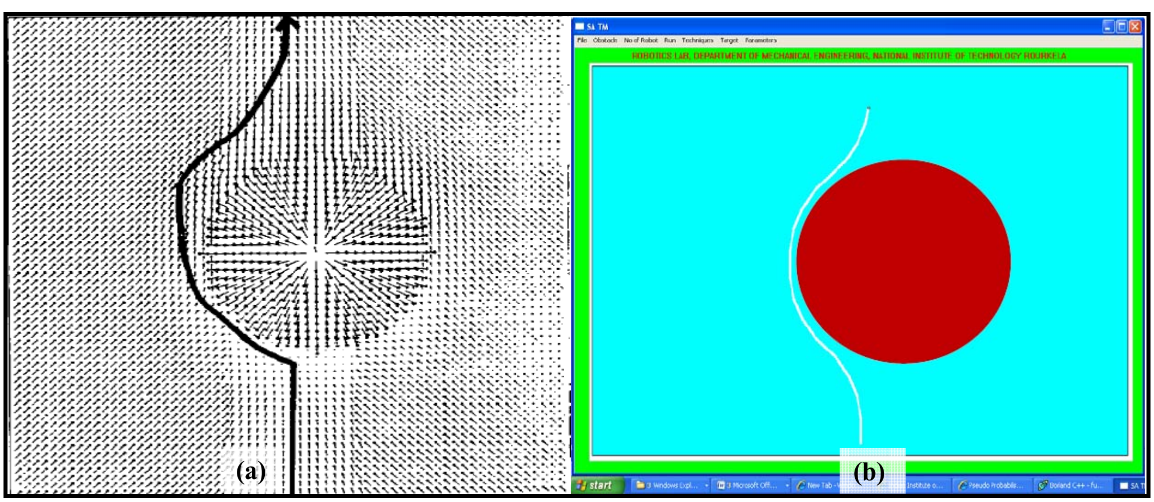


Figure 6.6. (a) Path traced by the robot embedded with Arkin's[211] controller, (b) Path traced by the robot embedded with proposed ANFIS controller.

A comparison has also been done between the results obtained by Camilo et al. [221] for navigation of mobile robot in a double U shaped environment and large and recursive U shaped environment and the results from the developed ANFIS method shown in Fig. 6.7 (a) and Fig. 6.7 (b). They show a very good agreement.

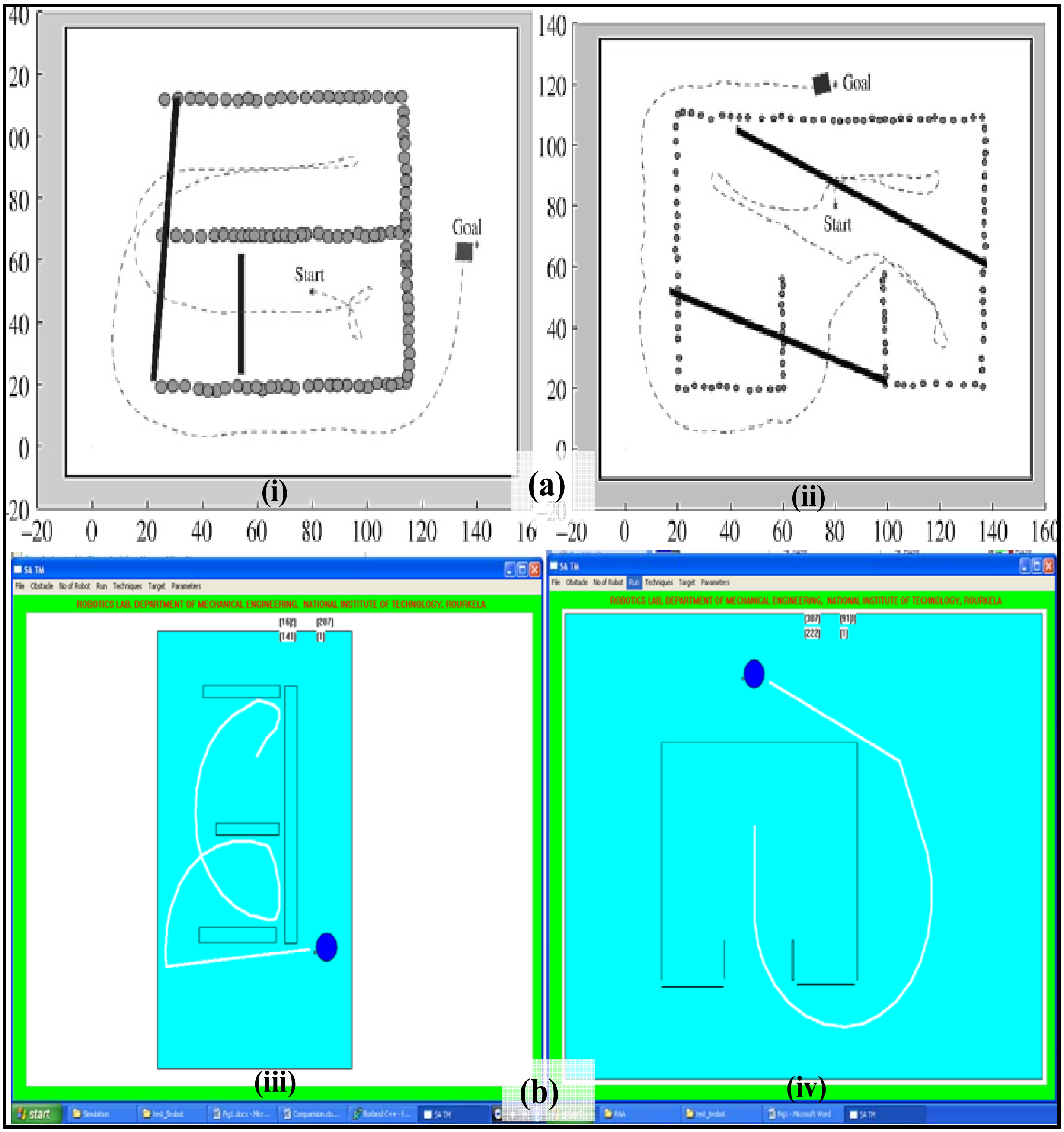


Figure 6.7. Comparison results of Camilo et al. [221] proposed approach (i) in a double U shape environment (ii) in a large and recursive U-shape environment (b) Results of proposed ANFIS approach (i) in a double U shape environment (ii) in a large and recursive U-shape environment.

6.4 Experimental Results

Experimental results are found out using Khepera-III mobile robot (Appendix-C.3) loaded simulation ROBNAV software (Appendix-A). The assumptions about the mechanical structure and the motion of a mobile robot are, the mobile robot moves on lab specified floor area and the wheel of a mobile robot rolls on the floor without any translational slip.

During experiment the paths followed by mobile robots to reach the target are traced. From the ANFIS (inputs: left, front, right obstacle distances and target angle) after learning, training and testing, robots gets the new steering angles. The experimental paths traced by the obstacle robots (OR) (Khepera-II (Appendix-C.2)) and target tracker robot (TTR) are marked on the floor by a pen as they move (Fig. 6.8). The OR1, OR2, OR3, OR4 are term as moving obstacle and TTR (Khepera-III) is terms as the target tracker. The paths followed by OR and TTR have been shown in Fig. 6.9. The results obtained from experimental setup are more close to results obtained from simulation mode (Fig. 6.10) which validate the proposed method.

During simulation and experimental result it has been found that the robot efficiently avoids the obstacles presents in the environment and successfully reach the targets. These robotics behaviours are verified in simulation and experimental mode (Fig. 6.10). Table 6.1 shows the times taken by the robots in simulations and in the experimental tests scenario during target finding. It is observed that the robots are able to reach the targets efficiently during simulation and experiment. It is found that the navigation of mobile robot with purposed ANFIS method has better performance than the fuzzy as well as neural controller in terms of positioning accuracy and collision avoidance.

Table 6.1 Time taken by robots in simulation and experiment to reach targets.

S. No.	**Observations (Fig.14)**	**Simulation environment**	**Experimental environment**	**Deviation of results (simulation Vs. experiment)**
01.	Length of path (in meter)	15.4	16.2	5.19%
02.	Time taken (seconds)	16.32	18.63	14.15%

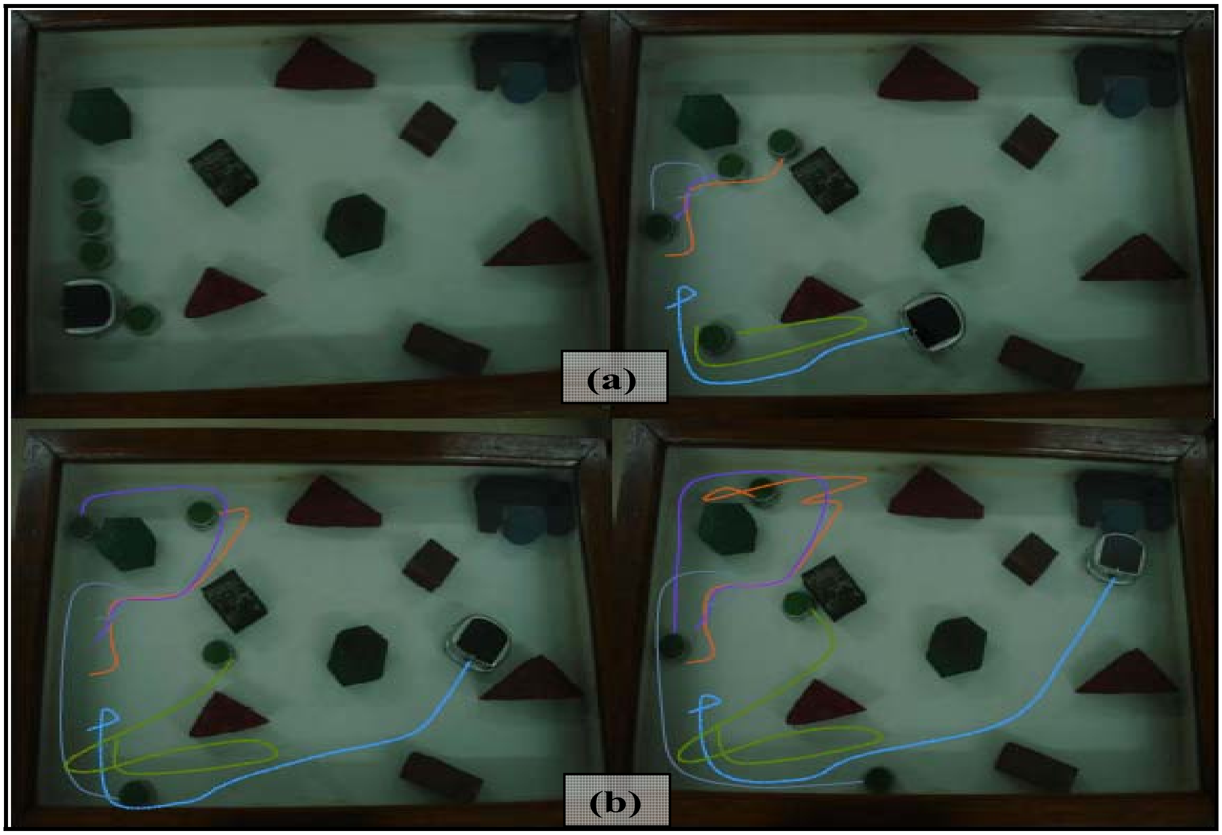


Figure 6.8. Experimental results of purposed ANFIS method.

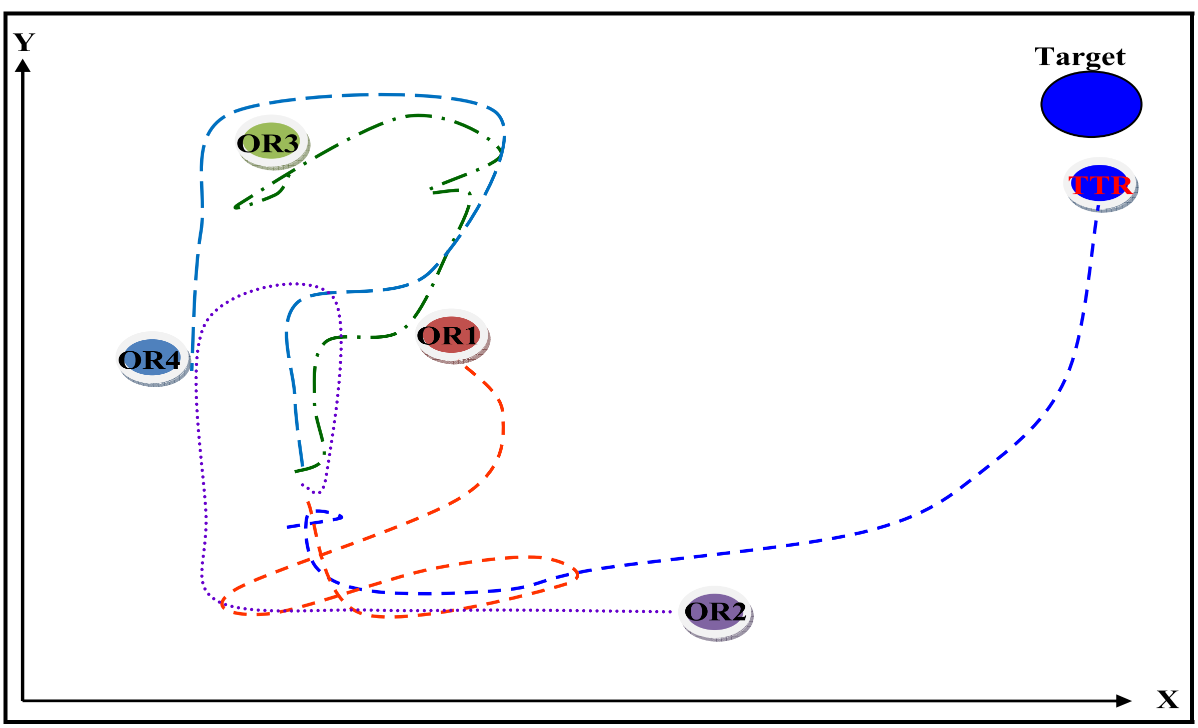


Figure 6.9. Paths followed by mobile robots using ANFIS method.

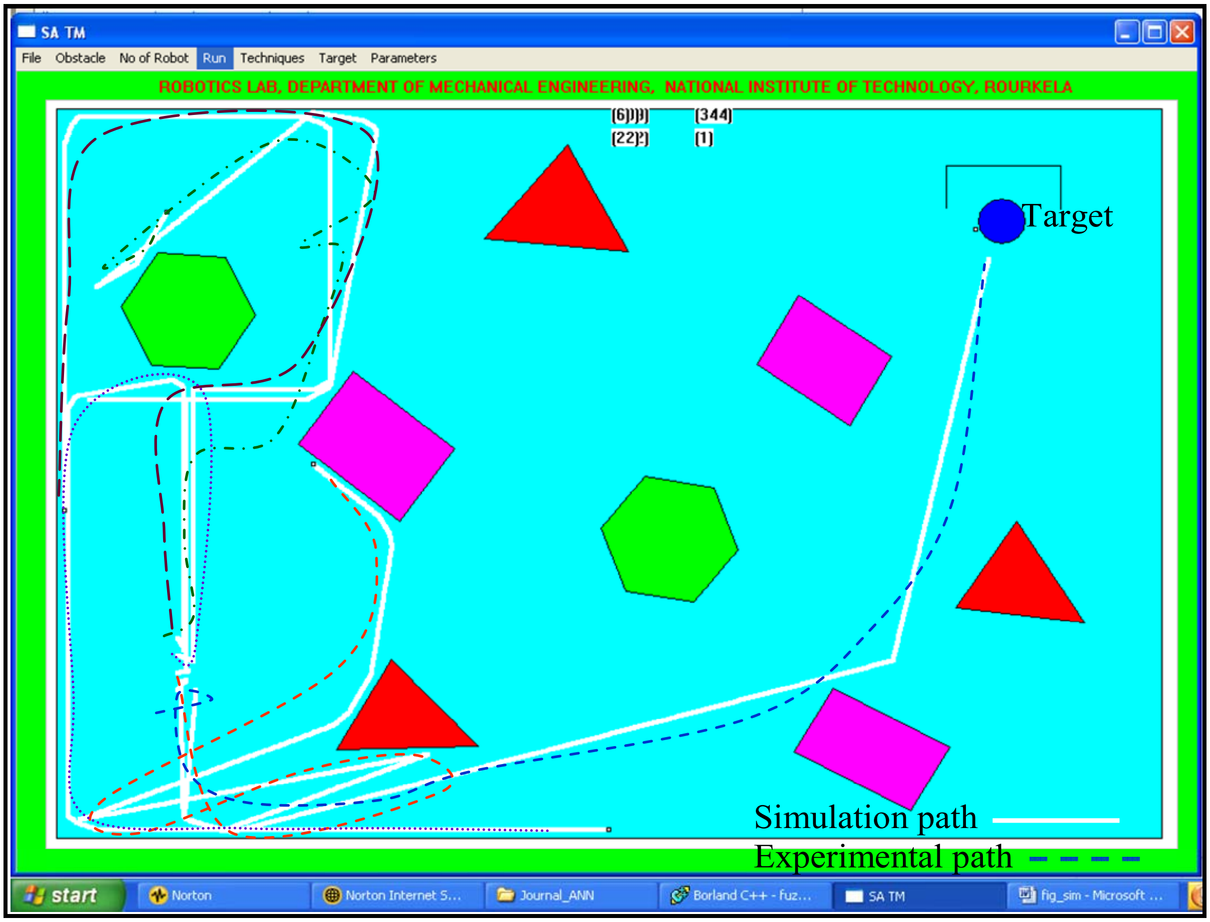


Figure 6.10. Experimental results validation in simulation mode.

6.5 Summary

The summary drawn on the basis of theoretical simulation and experimental analysis are depicted below:

The developed ANFIS controller has been used for navigation control of multiple mobile robots both in simulation and experimental mode. ROBNAV software has been developed to the handle the navigation control of mobile robot using ANFIS controller. The proposed method has got the following salient feature:

1. The proposed ANFIS controller is successfully applied for navigation in dynamic as well as static environments, mobile robot able to avoid static as well dynamic obstacle in a cluttered environment.

2. The robots are able to move in the surroundings using the embedded infrared sensors. The robot rapidly maps their surroundings which provide sufficient information for path optimization during navigation.
3. The proposed method is simple but efficient tool for mobile robot navigation, especially in a real world dynamic environment. Training patterns of each network can be generated by simulation rather than by experiment, saving considerable time and effort.

In the next chapter more robust hybrid technique has been discussed for better navigation control.

❖ Publications

1. "Navigational path analysis of mobile robots using ANFIS controller in dynamic environment", *Journal of Mechanical Engineering Science part C*, IMechE, 2009, (Accepted).
2. "ANFIS approach for navigation of mobile robots", *IEEE International conference on ARTCom09*, October 27–28, 2009, Kerela, India.
3. "Design of intelligent control systems for autonomous mobile robot navigation using soft computing" *GE Global Conference on DREAMS-07*, March 11, 2007, Banglore, India.
4. "Design of intelligent controller for mobile robot using soft computing", *National Conference on NCMSTA'08*, November 13-14, 2008, NIT Hamirpur, Himachal Pradesh, India.

7 Heuristic Rule Base Neural Controller for Mobile Robot

This chapter presents a novel technique for mobile robot to navigate in real world dynamic environment. When an autonomous mobile robot navigates in an unknown environment it requires to plan a path based on the information gathered from sensors in order to avoid obstacles and get to a target. This research is related to the idea of perception based heuristic rule formation for navigation of mobile robots in static as well as dynamic environments. The proposed method is simple and fast in execution using the concept from distance-transform path-finding algorithms. The proposed methodology provides a general, robust, safe and optimised path. The heuristic rule base network (HRBN) consists of a simple algorithm which makes predefined estimation function very smaller. The estimation function should be adequately defined for desired movement in the environments. A navigation system using rule based technique that allows a mobile robot to travel in an environment about, which the robot has no prior knowledge. This heuristic rule is applied in conjunction with artificial neural net work (ANN). The ANN is trained by back propagation algorithms (BPA). A HRBN provides an optimum trajectory which increases the effectiveness of a mobile robot. A Petri Net Model (PNM) has been used to prevent the inter robot collision during navigation. A series of simulations and experiments are conducted using the mobile robot to show the effectiveness of the proposed algorithm.

7.1 Introduction

Autonomous mobile robots have a wide range of applications in industries, hospitals, offices, and even in the military section, due to their superior and intelligent mobility. They are also useful in emergencies for fire extinguishing and rescue operations. Combined with manipulation abilities, their capabilities and efficiency will increase and can be used for dangerous tasks such as security guard, exposition processing, as well as undersea, underground and even space exploration [187]. In addition, their capabilities also allow them to carry out specialized tasks in hazardous or hardly accessible environments for human beings such as nuclear plants and chemical exposed environments. Motion planning algorithms construct such a path which deals with the planning of motion of a robot between starting positions to a target location [191]. This chapter introduces a control system for a mobile robot which provides heuristic learning concretely. Useful heuristic rules are hybridized with the ANN to build the desired mapping between perception and motion. ANN consisting of four inputs the left obstacles distances (Left-obs), right obstacles distances (Right-obs), front obstacles distances (Front-obs) and the interim steering angle and an output of final steering angle. To estimate the risk of colliding with other robots a petri net model (PNM) is used for the robot motions. It allows continuous, fast motion of the mobile robot without any need to stop for obstacles. This proposed approach has been tested in extensive simulation mode and implemented on Khepera III mobile robot as target tracker mobile robot and Khepera-II (Appendix-C.2) used as moving obstacle robot. In different experiments the proposed approach is well suited to control the motions of a team of robots in a typical environment and illustrate its advantages over other techniques developed so far. The hybrid path is much safer than the shortest path, but shorter than the safest one.

7.2 Perception Based Heuristic Rule

The heuristic rules are based on human perception (i.e. the working environment provides a fixed referential frame for the rules). In the current analysis the robot uses this environmental information to adjust itself according to it. This research goal is to obtain algorithms that, executed on a man-made visual system, result in the acquisition of perceptual capabilities that robot could use to perform specific commands [219]. Khepera III (Appendix-C.3) and Koala silver version (Appendix-C.4) mobile robot has been used for experimental validation. The Khepera III mobile robot has nine sensors placed around the robot and other two sensors are placed on the bottom. The sensors positions are numbered as shown in Fig. 7.1 (1to11). These sensors embed an infra-red light emitter and a receiver. This sensor device allows to measures the normal ambient light, which is strongly influenced by the robot's environment. Objects color, materials and surfaces do have an influence on the sensors response. In its base of the robot, five sensors are placed around the robot and are positioned and numbered as shown in Fig. 7.1(U1-U5), in fact five pairs of ultrasonic sensors where each pair is composed of one transmitter and one receiver. The ultrasonic sensors are powered by a 20 Vdc source. And Koala mobile robot has sixteen and sensors are placed around the robot. Their position and number are shown in Fig. 7.2 (L0 to L7 & R0 to R7). These sensors embed an infra-red light emitter diode and a receiver.

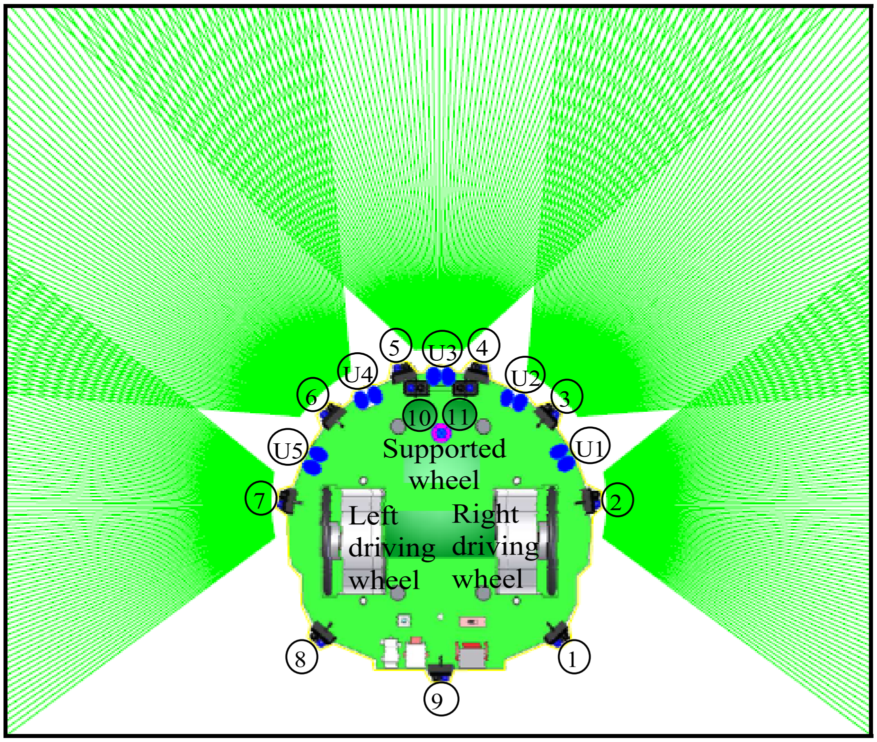


Figure 7.1. Position of wheels and sensors in Khepera-III mobile robot, infrared (1-11) and ultrasonic sensors (U1-U5).

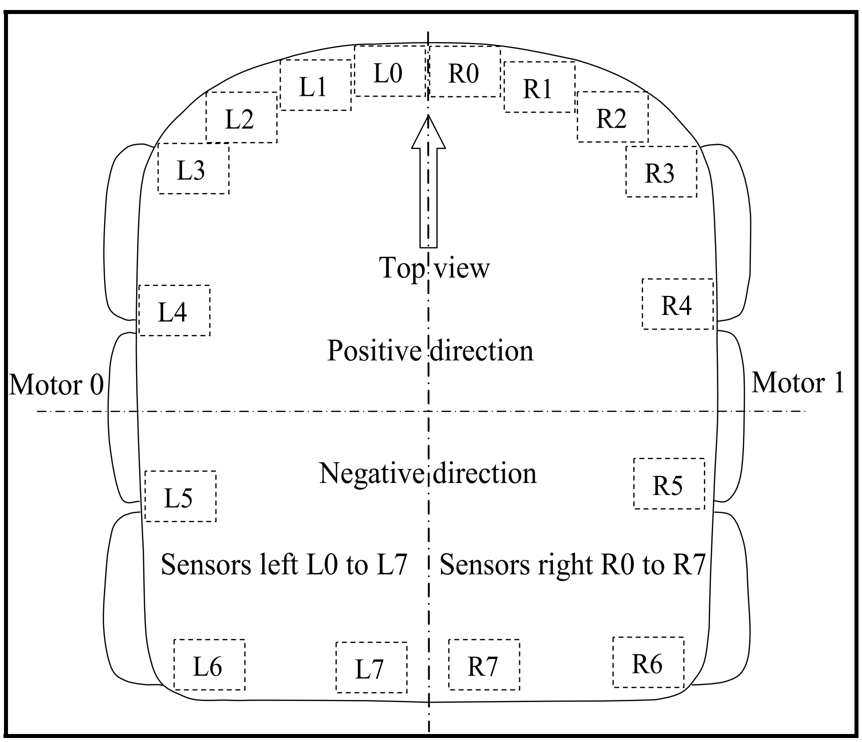


Figure 7.2. Position of wheels and sensors in koala mobile robot.

Based on these sensors a human perception based heuristic rule can be formulated. The methodology is a general, robust, and safer which provides fast path planning framework for robotic navigation. If the target is located right side then the robot will steer clockwise direction i.e. positive steering angle but it the target is located left side then the robot will steer counter clock direction i.e negative. Human perception based some of the heuristic rules from Table 7.1 are listed below based on the left obstacle and target both are situated in left side of the robot.

Rule 1: ***If*** left-obs = 150 mm and right-obs ≤ 200 mm and front-obs ≤ 200 mm and tar-ang = 82˚ ***Then*** change in steering angle = 0˚

Rule 2: If left-obs = 150 mm and right-obs ≤ 200 mm and front-obs ≤ 200 mm and tar-ang = 75˚ ***Then*** change in steering angle = -15˚

Rule 3: ***If*** left-obs = 150 mm and right-obs ≤ 200 mm and front-obs ≤ 200 mm and tar-ang = 54˚ ***Then*** change in steering angle = -30˚

Similarly rule can also formulate with reference to the obstacle as well as target are located in right side of the robot. Some of the heuristic rules from Table 7.2 are listed below.

Rule 7: ***If*** left-obs ≤ 200 mm and right-obs = 150 mm and front-obs ≤ 200 mm and tar-ang = 73˚ ***Then*** change in steering angle = 17˚

Rule 8: ***If*** left-obs ≤ 200 mm and right-obs = 150 mm and front-obs ≤ 200 mm and tar-ang = 51˚ ***Then*** change in steering angle = 31˚

Table 7.1. Heuristic rule formulation for obstacle and target located in the left side of the robot.

RuleNo.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
01	150	200	200	82	0
02	150	200	200	75	-15
03	150	200	200	54	-30
04	150	200	200	31	-30
05	150	200	200	37	-37

Table 7.2 Heuristic rule formulation for obstacle and target located in the right side of the robot.

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
06	200	150	200	70	0
07	200	150	200	73	17
08	200	150	200	51	31
09	200	150	200	31	27
10	200	150	200	38	38

Rule 9: ***If*** left-obs ≤ 200 mm and right-obs = 150 mm and front-obs ≤ 200 mm and tar-ang = 31˚ ***Then*** change in steering angle = 27˚

Some of the heuristic rules from Table 7.3 are listed below based on the obstacle presents in the front of the robot and target located in right side of the robot.

Rule 11: ***If*** left-obs ≤ 100 mm and right-obs ≤ 100 mm and front-obs = 1000 mm and tar-ang = 20˚ ***Then*** change in steering angle = 29˚

Rule 12: ***If*** left-obs ≤ 100 mm and right-obs ≤ 100 mm and front-obs = 800 mm and tar-ang = 22˚ ***Then*** change in steering angle = 34˚

Table 7.3. Heuristic rule formation for obstacle present front of the robot and target located in right side of the robot.

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
11	100	100	1000	20	29
12	100	100	800	22	34
13	100	100	600	24	41
14	100	100	400	26	51
15	100	100	200	28	72

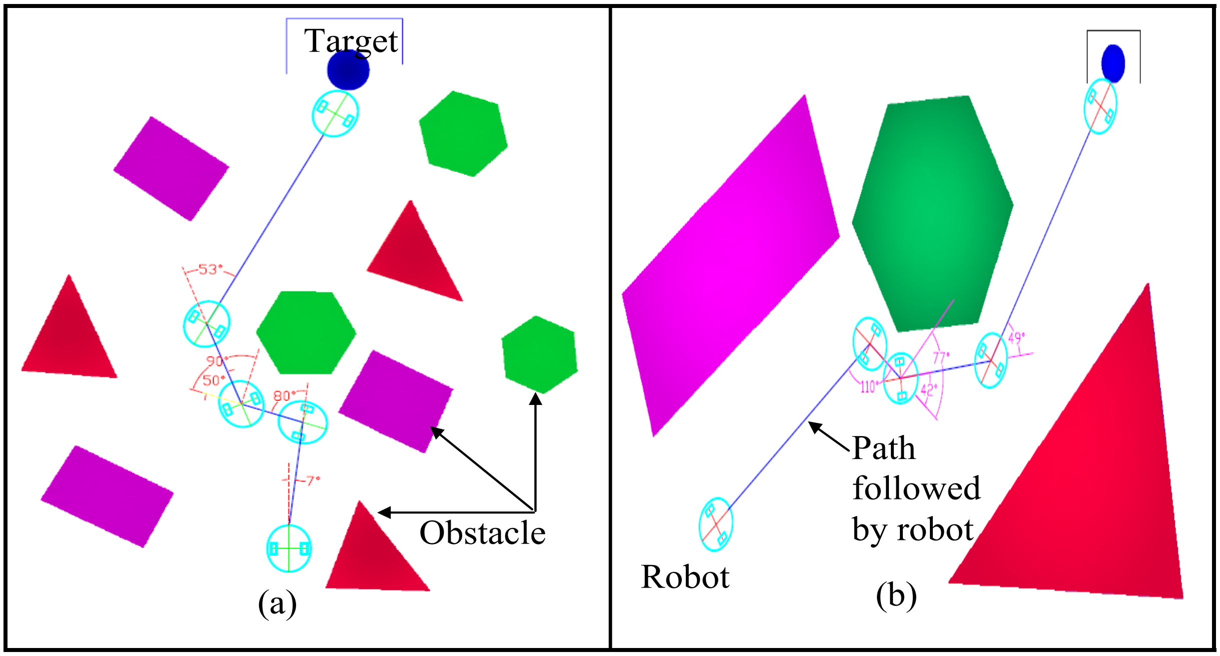


Figure 7.3. Perception based rule formation for obstacle avoidance in different environments.

Rule 13: ***If*** left-obs ≤ 100 mm and right-obs ≤ 100 mm and front-obs = 600 mm and tar-ang = 24˚ ***Then*** change in steering angle = 41˚

Fig. 7.3(a) depicts the environment to avoid the obstacles and motion control by the robots. Based on this scenario some formulated heuristic rules are listed in Table 7.4. These parameters can be used to generate different perception based heuristic rules, for example rule 16, 17 and 18 are given below.

Rule 16: ***If*** left-obs = 600 mm and right-obs = 150 mm and front-obs =600 mm and tar-ang = 7˚ ***Then*** change in steering angle = 7˚

Table 7.4. Perception based heuristic rule formation for obstacle avoidance Fig. 7.3(a)

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
16	600	150	600	7	7
17	700	150	150	0	-80
18	515	150	550	90	50
19	420	150	440	53	53

Table 7.5. Perception based heuristic rule formation for obstacle avoidance (Fig.7.3(b))

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
20	460	1650	1480	0	0
21	430	1100	200	0	110
22	100	810	850	-77	-42
23	70	420	1000	-49	-49

Rule 17: ***If*** left-obs = 700 mm and right-obs = 150 mm and front-obs = 150 mm and tar-ang = 0˚ ***Then*** change in steering angle = -80˚

Rule 18: ***If*** left-obs = 515 mm and right-obs = 150 mm and front-obs = 550 mm and tar-ang = 90˚ ***Then*** change in steering angle = 50˚

Similarly Fig. 7.3(b) depicts the different environment to avoid the obstacles and motion control by the robots. Based on this scenario some formulated heuristic rules are listed in Table 7.5. These parameters can be used to generate different perception based heuristic rules, for example rule 20, 21 and 22 are given below.

Rule 20: ***If* left-obs** = 460 mm and right-obs = 1650 mm and front-obs =1480 mm and tar-ang = 0˚ ***Then*** change in steering angle = 0˚

Rule 21: ***If*** left-obs = 430 mm and right-obs = 1100 mm and front-obs = 200 mm and tar-ang = 0˚ ***Then*** change in steering angle = 110˚

Rule 22: ***If*** left-obs = 100 mm and right-obs = 810 mm and front-obs = 850 mm and tar-ang = -77˚ ***Then*** change in steering angle = -42˚

Based on Fig. 7.4(a) illustrates the environment if the robot enters into U shaped wall, in such a situation, the robot keep on heading towards the goal position. But when it moves towards the goal position, it also comes closer to the obstacles. Any obstacle-avoidance behaviour except wall-following behaviour would make the robot divert from its goal position. To avoid such situation some of the rules are listed in Table 7.6. These parameters can be used to formulate heuristic rule for wall following, for example rule 25, 26 and 27 are given below.

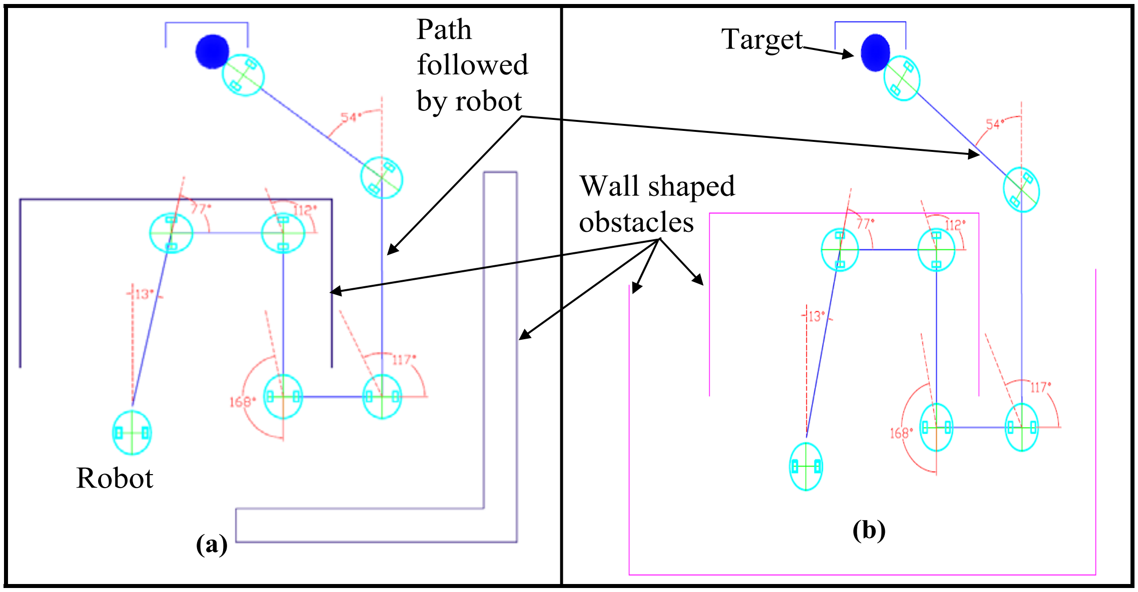


Figure 7.4. Perception based rule formation for wall following behaviour in different environments

Rule 25: ***If*** left-obs = 780 mm and right-obs = 835 mm and front-obs = 200 mm and tar-ang = 0˚ ***Then*** change in steering angle = 77˚

Rule 26: ***If*** left-obs = 80 mm and right-obs = 1510 mm and front-obs = 285 mm and tar-ang = -112˚ ***Then*** change in steering angle = 90˚

Rule 27: ***If*** left-obs = 155 mm and right-obs =1490 mm and front-obs=660 mm and tar-ang = 168˚ ***Then*** change in steering angle = -90˚

Table 7.6. Human perception based heuristic rule formation for wall following Fig. 7.4(a)

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
24	680	1160	1220	13	13
25	780	835	200	0	77
26	80	1510	285	-112	90
27	155	1490	660	168	-90
28	250	530	1085	-117	90
29	235	515	No obstacle	-54	-54

Table 7.7. Perception based heuristic rule formation for wall following (Fig. 7.4 (b))

Rule No.	Left-obs (millimeter)	Right-obs (millimeter)	Front-obs (millimeter)	Tar-ang (Degree)	Steering angle (Degree)
30	1100	1890	2070	13	13
31	780	835	80	0	77
32	80	1630	130	-112	90
33	1000	2000	660	168	-90
34	250	530	1085	-117	90
35	235	515	No obstacle	-54	-54

Similarly Fig. 7.4(b) illustrates the other wall shaped environment. To avoid such situation some of the rules are listed in Table 7.7. These parameters can be used to formulate heuristic rule for wall following, for example rule 30, 31 and 32 are given below.

Rule 30: ***If*** left-obs = 1100 mm and right-obs = 1890 mm and front-obs = 2070 mm and tar-ang = 13˚ ***Then*** change in steering angle = 13˚

Rule 31: ***If*** left-obs = 780 mm and right-obs = 835 mm and front-obs = 80 mm and tar-ang = 0˚ ***Then*** change in steering angle = 77˚

Rule 32: If left-obs = 80 mm and right-obs =1630 mm and front-obs=130 mm and tar-ang = -112˚ ***Then*** change in steering angle = 90˚

Rule 32: If left-obs = 80 mm and right-obs =1630 mm and front-obs=130 mm and tar-ang = -112˚ ***Then*** change in steering angle = 90˚

The rules used for navigation of mobile robots are generated by induction from examples. Approximately one thousand five hundred rules are fed into the induction program, within the Clementine data ROBNAV software package. The examples present the situations encountered by a robot while moving in a multi-robot, highly cluttered environment, and the actions that each robot has to take to avoid colliding with other robots as well as with static obstacles. The velocity of the robot motion is decided on the steering angle which in tern is related to the position of the obstacles around. For higher values of steering angle the turning velocity is more.

7.3 Back Propagation Algorithms (BPA)

A back-propagation algorithm has been used to calculate the gradient of the error of the network with respect to the network's modifiable weights. This gradient is almost always then used in a simple stochastic gradient descent algorithm to find weights that minimise the error. Back-propagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited. The network is trained to navigate by presenting it with 200 patterns representing typical scenarios, some of which are depicted in Fig. 7.5. These parameters can be used to formulate heuristic rules for obstacle avoidance, wall following and target searching behaviours. The number of hidden nodes depends upon the number of training patterns. For the current analysis two layers of hidden nodes are taken so that the output is within the error limit and the deviation between desired output and actual output, of the neural network converges to minimum threshold value during training. The training error is the difference between desired output and actual output. The “first steering angle” is the “interim steering angle” and is one of the inputs to neural network in the hybrid controller. Some rules are listed in section 7.2. The training pattern is similar to depicted in chapter 5 section 5.2.

7.4 Petri Net Model (PNM)

The Petri Net Plans framework (PNPs) allows the representation of high level programs for robotic behaviour, providing all the action features needed to describe complex plans in dynamic, partially observable and unpredictable environments (Fig.7.6).The multi-robot extension of PNPs allows the synchronization of actions among different robots, the performance of deliberate cooperation and the cooperative handling of local failures in a multi-robot system. A multi-robot PNP is automatically divided by each single robot of the system for the individual execution. The robots perform their actions relying on their individual knowledge base, and during the plan execution they are able to communicate through a reliable channel, to attain synchronization and sharing of information. Fig. 7.6 depicts the petri net model built into each robot to enable it to avoid collision with other robots. The model comprises 6 states (or Tasks). The location of the token indicates the current state of the robot. It is assumed that, initially, the robots are in a highly cluttered environment, without any prior knowledge of one another or of the targets and obstacles. This means the robot is in state "Task 1" ("Wait for the start signal").

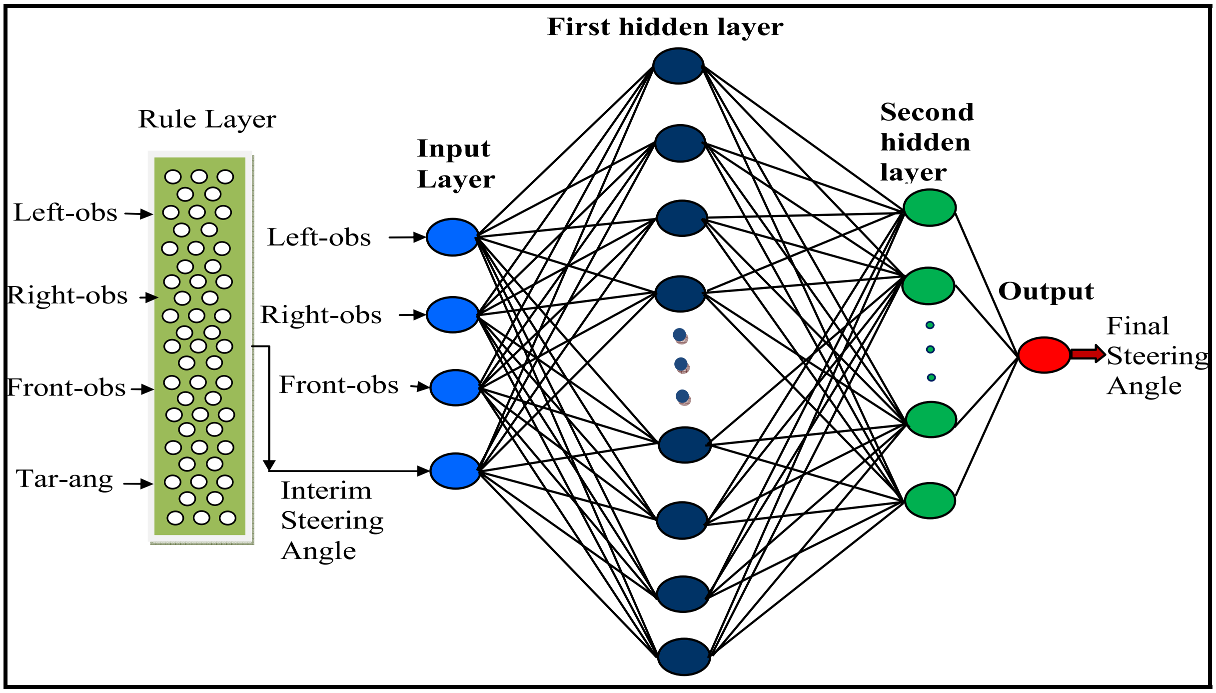


Figure 7.5. Four-layer heuristic rule neural network for robot navigation.

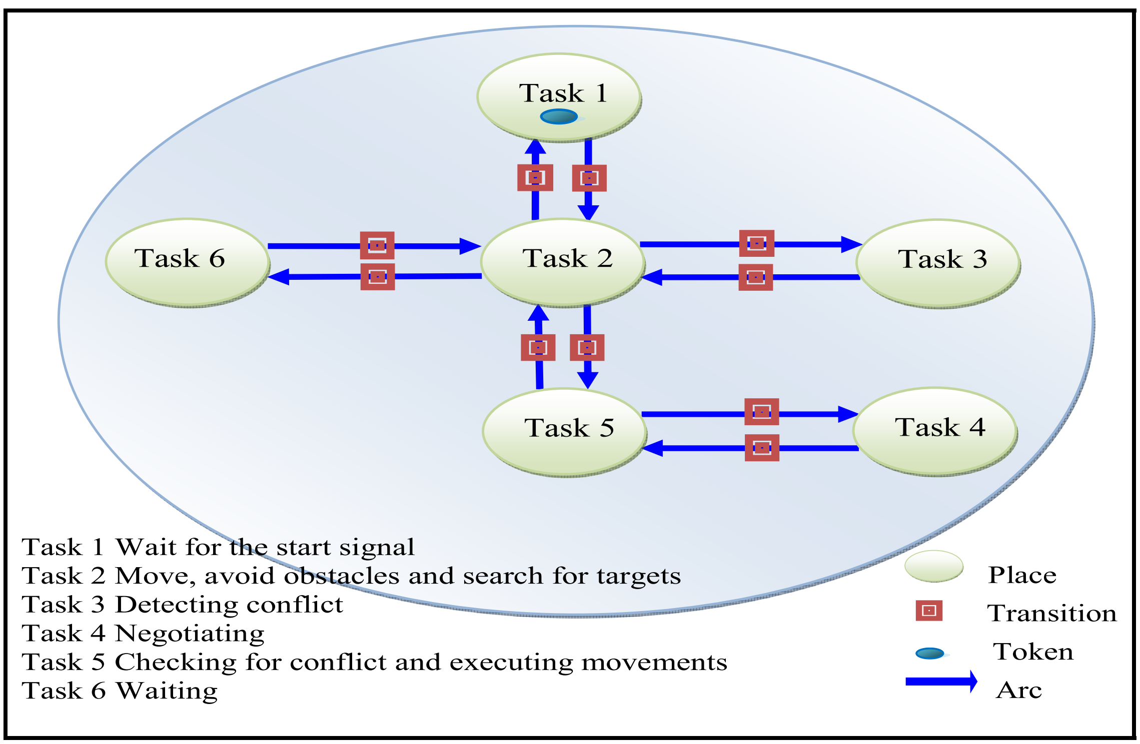


Figure 7.6. Petri net model to avoid inter collision among robots during navigation.

In Fig. 7.6, (Appendix-B) the token is in place “Task 1”. Once the robots have received a command to start searching for the targets, they will try to locate targets while avoiding obstacles and one another. The robot is thus in state “task2” (“Moving, avoiding obstacles and searching for targets”). During navigation, if another robot obstructs the path of a robot, then a conflict situation is raised. (State “Task 3”, “Detecting Conflict”). Conflicting robots will negotiate with each other to decide which one has priority. The lower priority robot will be treated as a static obstacle and the higher priority robot as a proper mobile robot (state “Task 4”, “Negotiating”). As soon as the conflict situation is resolved, the robots will look for other conflicts and if there is no other conflict they will execute their movements (state “Task 5”, “Checking for conflict and executing movements”). If a robot meets two other robots already in a conflict situation, then its priority will be lowest and it will be treated as a static obstacle (state “Task 6”, “Waiting”) until the conflict is resolved. When this is done, the robot will re-enter state “Task 2”. The dynamic and asynchronous structure of the PNM is ideally suited for the modeling of multiple mobile robots to provides inter collision avoidance among robots and also helps to find the target.

7.5 Simulation Results and Discussion

The series of simulations test has been conducted using ROBNAV software (Appendix-A). To demonstrate the effectiveness and the robustness of the proposed method, simulation results on mobile robot navigation in various environments are exhibited.

The obstacle avoidance behaviour is activated by using perception base rule introduced into the software as discussed in section 7.2. When arrays of sensor receive the information of object (which is too close to the robot), it avoids a collision by moving away from it in the opposite direction. In this case, the obstacle avoidance behaviour is activated when the readings from any sensors are less than the minimum threshold values. The simulation result obstacle avoidance and inter collision avoidance among mobile robot has been shown in Fig. 7.7. The wall following behaviour is activated by using perception base rule introduced into the software as discussed in section 7.2. i.e. the mobile robot detects an obstacle in the front while the target tracking control mode is on operation. In this case, the wall following behaviour is activated i.e. The mobile robot rotates clockwise or counterclockwise such that it can align and move along the wall shown in Fig. 7.8.

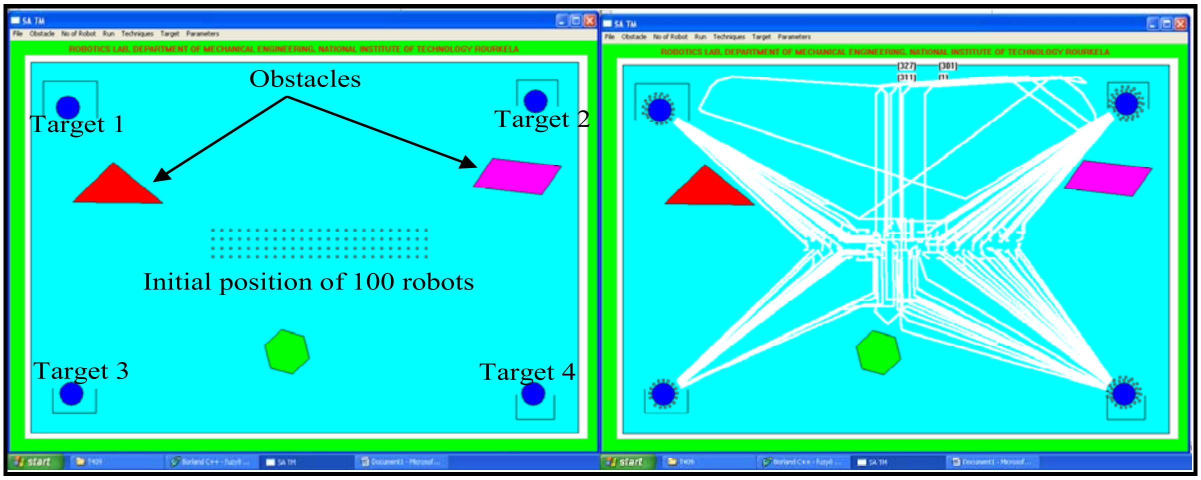


Figure 7.7. Simulation result of inter robot collision avoidance among robots via petri net model (a) Initial position of mobile robots (b) After simulation result.

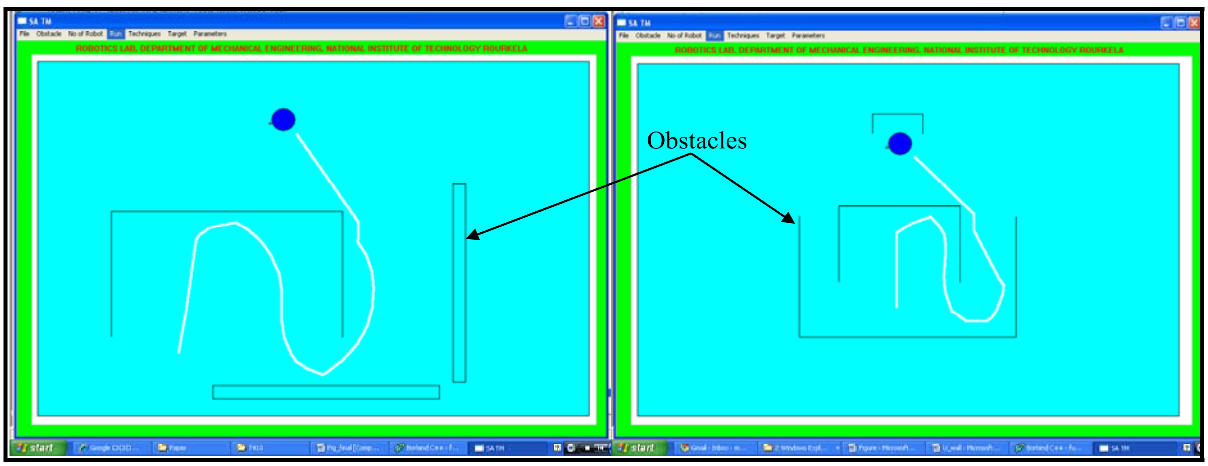


Figure 7.8. Simulation result of wall following behaviour in different environments.

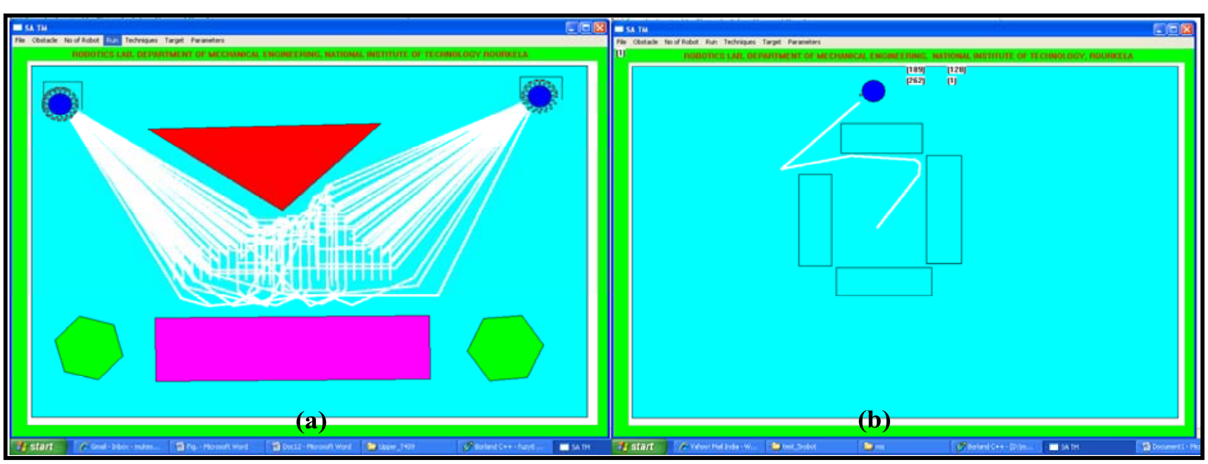


Figure 7.9. (a) Simulation result of target searching behaviour of mobile robots (b) target searching behaviour.

When the acquired information from the sensors tracks the target and shows that there are no obstacles around robot, its main reactive behaviour is target steer. HRBN mainly adjusts robots motion direction and quickly moves it towards the target if there are no obstacles around the robot as shown in Fig. 7.9 (a). In the proposed control strategy, human perception based heuristic rules are formulated and PNM is used to provide inter collision of robot as well as to find the target which has been trained by ANN using back propagation algorithms. The target searching behaviour has been demonstrated in Fig. 7.9(b) it has found that it is more reliable in position accuracy than the other approaches. The results from the proposed method for real time navigation of mobile robot have been compared with the result from obtained by Ayari et al. [220] for navigation of mobile robot in collision free goal reaching in learned environment and the results from the developed HRBN method (Fig. 7.10).

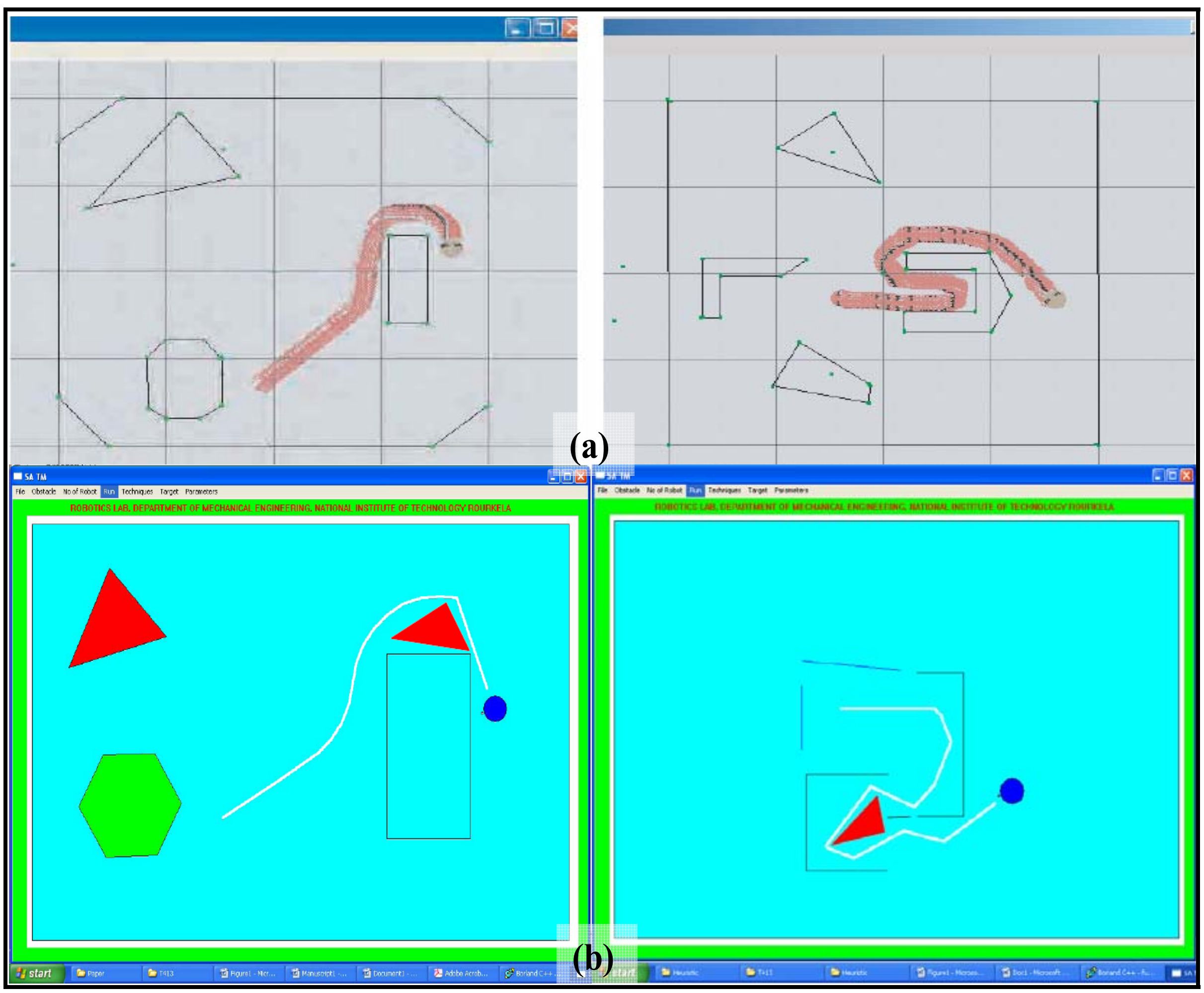


Figure 7.10. (a) Simulation results of Ayari et al. [220] collision free goal reaching in learned environment (b) Simulation results of proposed method collision free goal reaching.

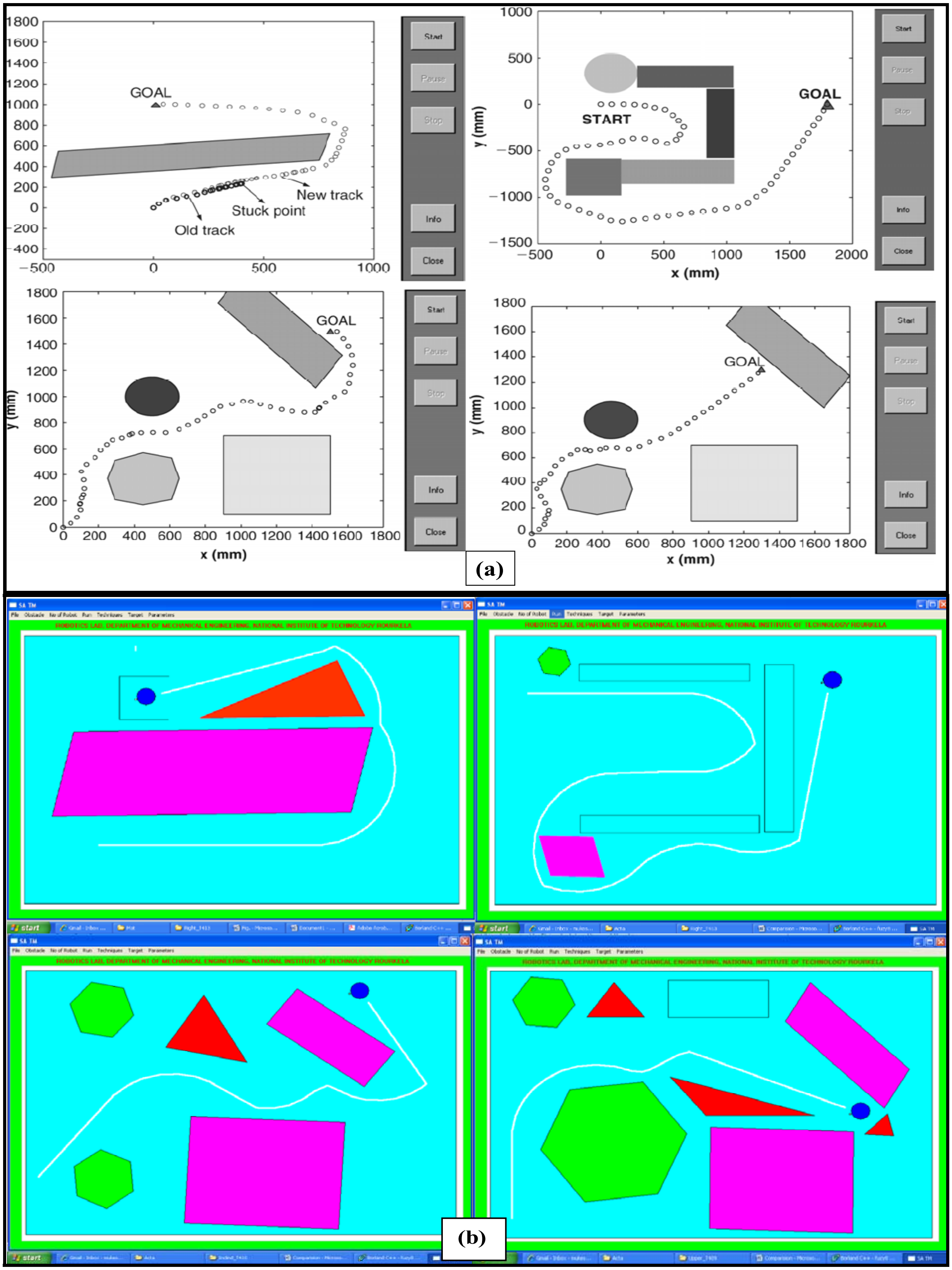


Figure 7.11. (a) Simulation results comparisons with Yang et al. [88] (b) Simulation results of proposed method.

The proposed methodology has been also compared between the results obtained by Yang et al. [88] for navigation of mobile robot in collision free goal reaching and the results from the developed HRBN method (Fig. 7.11). The effectiveness of the developed controller has been verified both in simulation and real mode and they are in good agreement. The effectiveness of the developed controller has been verified both in simulation and real mode and they are in good agreement.

7.6 Experimental Results with Real Mobile Robot

The effectiveness of the proposed method has been verified in a series of practical tests on Khepera-III and Koala mobile robot. The developed ROBNAV software (Appendix-A) used for simulation test is loaded into the mobile robot to obtain experimental result. The assumptions about the mechanical structure and the motion of a mobile robot to which our proposed method is applied as mobile robot moves on lab specified floor area and the wheel of a mobile robot rolls on the floor without any translational slip.

7.6.1 Implementation of HRBN Controller on Khepera robot

To exhibit the experimental test of multiple mobile robot the developed software ROBNAV is loaded into the Khepera-II and Khepera-III mobile robot. The Khepera-III mobile robot is the main robot which is termed as target tracker robot (TTR) which are able to track the target where as Khepera-II mobile robot is termed as moving obstacle robot (OR) which is not suppose to track the target.

From the human perception based HRBN consist of four inputs left, front, right obstacle distances and interim steering angle after learning, training and testing, robots gets final steering angles as an output. The paths traced by the obstacle robots (OR) and target tracker robot (TR) on the floor as they move is shown in Fig. 7.12. The OR1, OR2, OR3, OR4 (Khepera-II), are termed as moving obstacle and TR (Khepera-III), is termed as the target tracker. The paths followed by OR and TR have been shown in Fig. 7.13. It has been found that the results obtained from experimental setup are more close to results obtained from simulation mode which validate the proposed method (Fig. 7.14). From these figures, it has been seen that the robots can indeed avoid obstacles and reach the targets.

Figure 7.12. Experimental validation of simulation result on Khepera robots

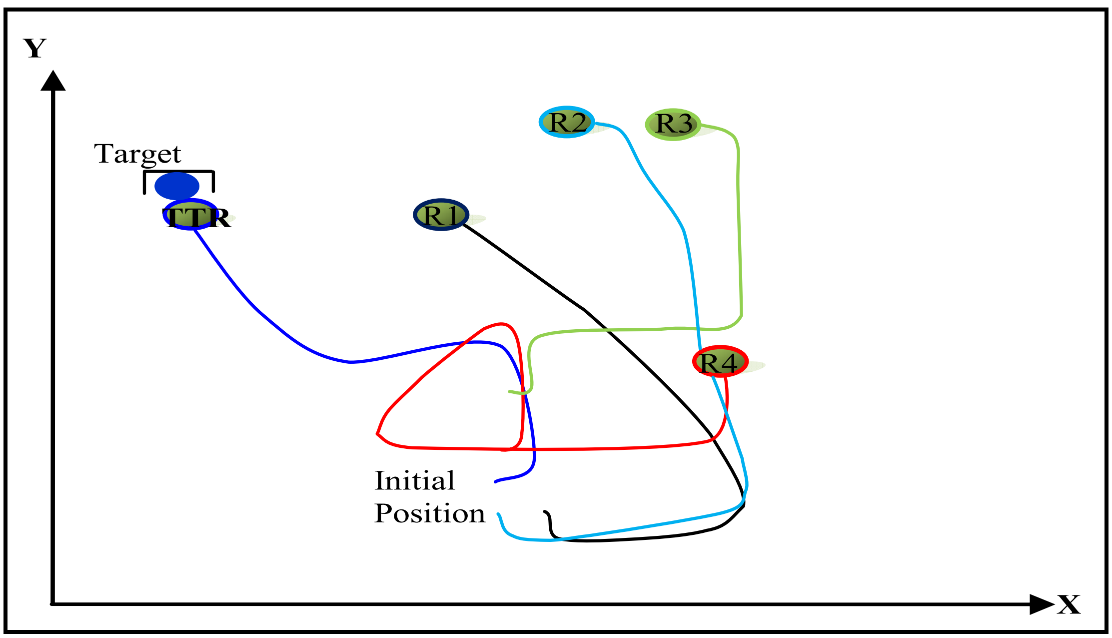


Figure 7.13. Traced paths of mobile robots during experiment

Table 7.8 shows the times taken by the robots in simulations and in the experimental tests scenario during target finding. It is observed that the robots are able to reach the targets efficiently during simulation and experiment. This method provides much faster response in an unknown environment and is less computational effort than other conventional approaches. This chapter contributes to the efforts of developing practical, modular, and easy-to-implement robot navigation algorithms that are both cost and computationally effective.

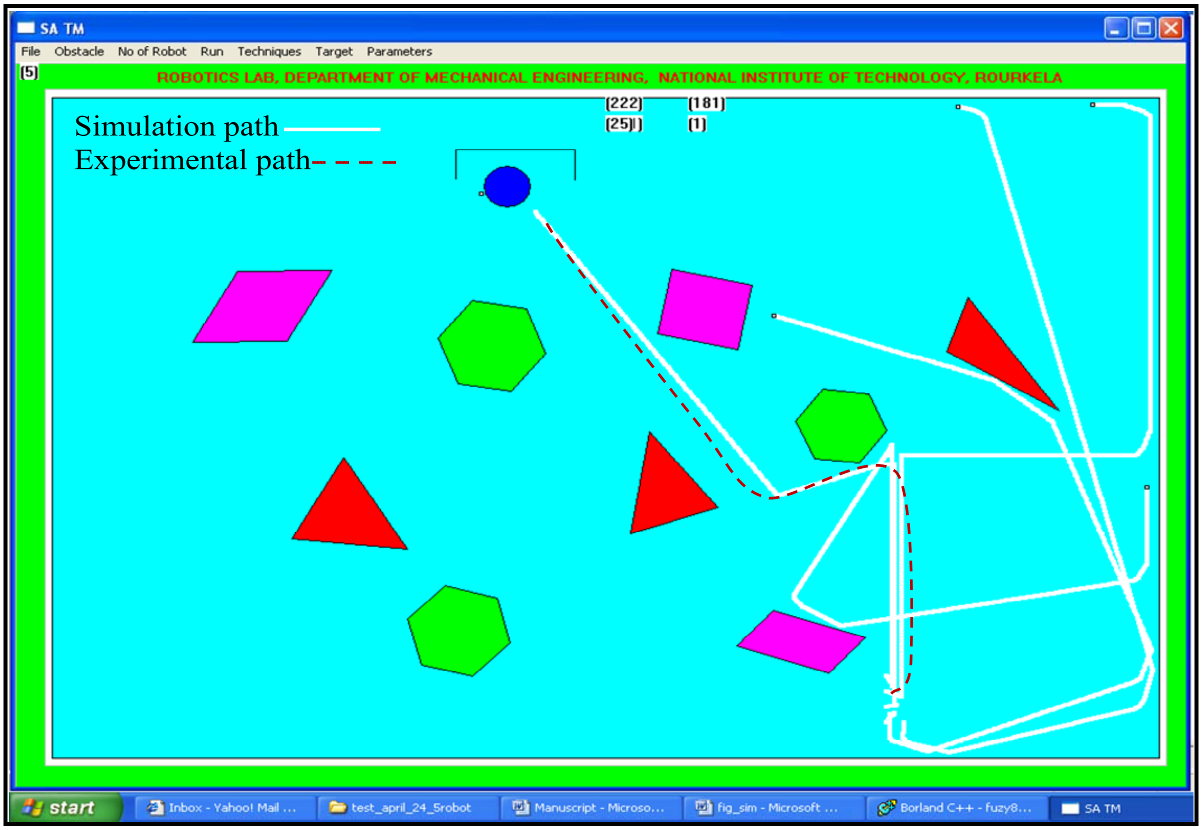


Figure 7.14. Path optimization of target tracker robot (TR) avoiding static as well as dynamic obstacle with experimental validation.

Table 7.8 Total path traveled and time taken by robots during simulation and experimental environment by proposed method.

S.No.	Observations (Fig.7.15)	Simulation environment	Experimental environment	Deviation of results (simulation Vs. experiment)
+01	Length of path (in mm)	10750	11300	05.12%
02	Time taken (seconds)	11.40	12.99	13.99%

7.6.2 Implementation of HRBN Controller on Koala robot

To perform the experimental test of mobile robot the developed software ROBNAV (Appendix-A) is loaded into the Koala robot mobile robot. The sensors position has been illustrated in Fig. 7.2. To control the functionalities of the Koala robot (motors, sensors etc.), a set of command are implemented in the control protocol.

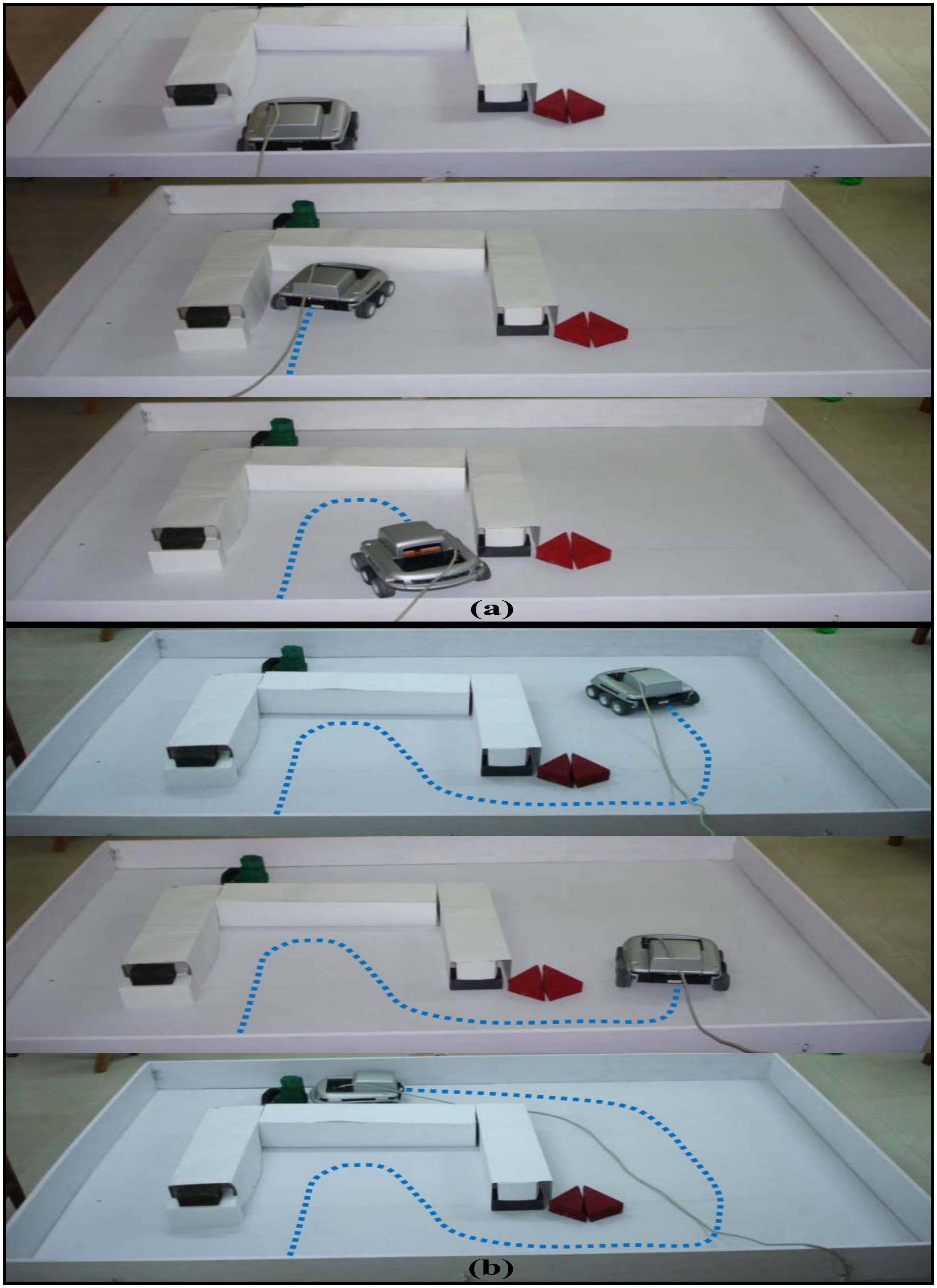


Figure 7.15. (a) Experimental result with Koala mobile robot to start moving towards target and (b) Finally robot tracks the target following optimal path.

From the human perception based HRBN consist of four inputs left, front, right obstacle distances and first steering angle after learning, training and testing, robots gets final steering angles as an output. The path traced by the robots on the floor as they move is shown in Fig.7.15 (a) and Fig.7.15 (b). It has been found that the results obtained from experimental setup are more close to results obtained from simulation mode which validate the proposed method (Fig. 7.16). Table 7.9 shows the times taken by the robots in simulations and in the experimental tests scenario during target finding.

Table 7.9. Total path traveled and time taken by robots during simulation and experimental environment by proposed method

S.No.	**Observations (Fig.7.17)**	**Simulation environment**	**Experimental environment**	**Deviation of results (simulation Vs. experiment)**
01	Length of path (in mm)	21750	23530	08.18%
02	Time taken (seconds)	23.05	25.65	11.27%

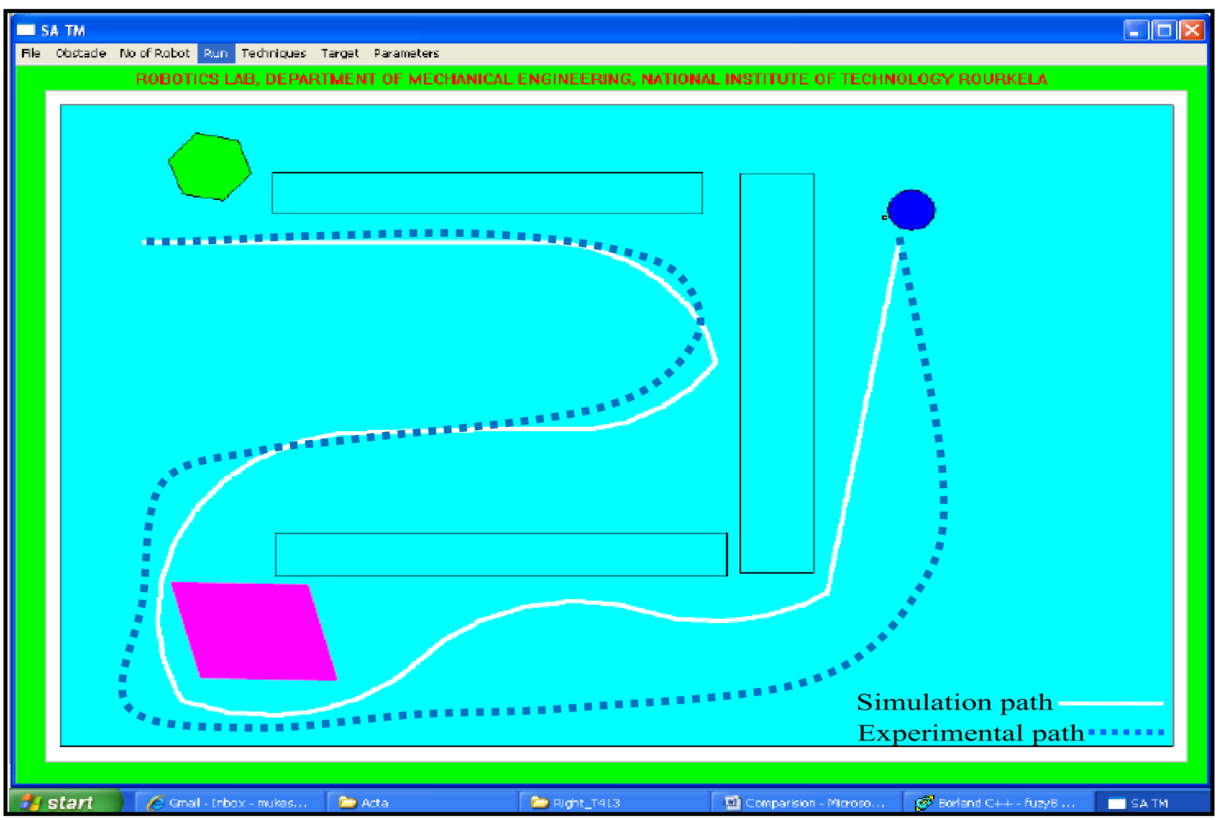


Figure 7.16.Experimental result validation with simulation mode.

7.7 Summary

This chapter proposed a new human perception based control law for nonholonomic wheeled mobile robot. From the theoretical, simulations and experimental analyses the following conclusion can be drawn:

1. The methodology is a general, robust, and safest which provides fast path planning framework for robotic navigation using human perception based HRBN. The developed method is simple and efficient tool for mobile robot navigation, especially in a real world dynamic environment.
2. It is successfully applied for navigation in dynamic as well as static environments. The robot rapidly recognises their surroundings which provide sufficient information for path optimization during navigation.
3. The proposed methodology is successfully applied for navigation in dynamic as well as static environments. The robot rapidly recognises their surroundings which provide sufficient information for path optimization during navigation. Training patterns of ANN can be generated by simulation rather than by experiments, saving considerable time and effort.
4. Comparison of results between the current developed and with other techniques have shown good agreement. This validates the authenticity of the proposed technique.
5. The presented motion planner has demonstrated its effectiveness in planning for multiple mobile robots within a bounded workspace. It is planned with a high probability of success, even in cluttered environments involving robots, stationary obstacles and moving obstacles.

This chapter depicts a methodology to achieve the co-operation navigation in pragmatic way.

❖ Publication

"Heuristic rule base hybrid neural network for navigation of mobile robot", *Journal of Engineering Manufacture Part B*, IMechE, 2009, (Accepted).

8 Results and Discussion

This investigation discusses the development of autonomous navigation and obstacle avoidance systems for differential drive mobile robots operating in unstructured real world dynamic environments. In this chapter the performance of developed intelligent controllers are summarised and their results are outlined.

8.1 Kinematics and Dynamic Stability of Mobile Robot

The kinematic design is a basic part of the mobile robot system. Improved mechanical designs and mobility control systems will enable the mobile robot to navigate in no marked paths and for autonomous operation. A kinematic methodology is the first step towards achieving these goals.

In chapter three, the advance kinematic modeling of mobile robot, from the motivation of the kinematic methodology through its development and applications has been proposed. The kinematic modeling of the wheels, robot coordinate systems and positions on the robot has been developed and discussed. The presented kinematic methodology provides valuable insights into these areas. Just as the mobility characterization tree allows determining the motion characteristics of an existing mobile robot, this may utilise the tree to design mobile robots to possess such desired characteristics as two or three degree of freedoms. It is concluded that a mobile robot having two diametrically opposed driven wheels is ideal for this application because of the simplicity of its mechanical design and kinematic model. Similarly, the sensing characterization tree may be applied to design a mobile robot with a robust sensing structure to minimise the adverse effects of wheel slip on the calculation of the mobile robot position. It is noted that the set of actuated wheel variables and sensed wheel variables cannot coincide if both robust actuation and robust sensing are desired for kinematic modeling of mobile robots is the first step towards, designing feedback control systems. The developed kinematic calculations of positions, velocities and accelerations can be applied to calculate the dynamic forces and torques produced by the motion of the robot components. For example, the recursive Eular langrage dynamics formation applies kinematics to propagate positions, velocities and accelerations from the robot wheel to the robot base.

8.2 Intelligent Controller of Mobile Robots

The intelligent controller plays an important role in path analysis and planning of the mobile robots. The obstacle avoidance, wall following, target searching and collision free navigational path depends on intelligence of the controller. The control techniques are a very important area of research in the field of mobile robot navigation. This thesis presents new techniques to for intelligent navigational controller.

Before the introduction of learning algorithms into the fuzzy controller the relationships between the neural controller and the fuzzy controller can be viewed as two extreme endpoints on a spectrum of designing approaches. At one end fuzzy controller has meaningful representations fuzzy if then rules and fuzzy reasoning derived from human expertise but it has no adaptive capability learning from examples to take advantage of a desired input output data set. At the other end neural controller represents a totally different paradigm with learning capability that adapts its parameters based on desired input output pairs but neither can it accommodate a priori knowledge from human experts nor can we transform network configurations and connection weights into a meaningful representation to account for structured knowledge. Conceptually this may say that designing of fuzzy controller is a top down approach which employs high level knowledge rules to describe a system while neural controller is a bottom up approach which uses low level knowledge input output pairs to tackle the same problem. In some cases fuzzy controller has gained an advantage over neural controller that is the knowledge representation feature that can both speed up learning by encoding prior knowledge in the form of fuzzy if then rules into parameters and interpret the parameters after learning by transforming the parameters back to fuzzy if then rules. The basic learning rule of fuzzy controller is of gradient descent type which is the same as that of neural controller. In some situation the neural controllers do not rely on the system model, they are suitable for uncertain and highly nonlinear situations. Moreover, neural controller has strong parallel processing, adaptive and learning capabilities, thus they are popular in the design of robot controllers. This fact allows these two modeling approaches to benefit from research findings and results in both literatures. To get the advantages of both an adaptive neuro fuzzy controller has been proposed, which integrates the fuzzy logic representation of human knowledge with the learning capability of neural networks, to solve the dynamic control of mobile robot navigation problems.

In chapter four, a theoretical development of a complete navigation procedure of a mobile robot in an unknown and cluttered environment has been illustrated. To formalize the imprecise reasoning processes, a method using a fuzzy logic technique has been presented. Intuitively, this would result in a more robust and accurate model, which is also easily interpretable. The model has been fine tuned using behaviour based control. A Mamdani fuzzy system has been used for design of intelligent controller that is more compatible with the reasoning process of human behaviours. A new method of obstacle avoidance, wall following as well as target searching behaviour has been presented in this chapter as part of the navigational procedure. The behaviour-based mobile robot developed in this study has several levels of competence. This allows a reactive control, which results in an efficient behaviour towards unforeseeable situations. The problem of extracting the IF–THEN rule base has been carried out via an evolutionary programming method. Simulations were carried out on a nonholonomic mobile robot to test the performances of the proposed fuzzy controller. The theoretical analysis provides the requirements for the design of a suitable fuzzy rule base, in order to guarantee the asymptotical stability of the robot system. Simulation and experimental studies on the developed fuzzy controller of the robot system are conducted to investigate the system performance. The presented extensive experiments shows that the developed behaviour robot is capable of achieving the desired turn angle and making the mobile robot follow the target by avoiding static as well as dynamic obstacle satisfactorily. The proposed methodology has been compared with previous work presented by many researchers, it is found that the method of designing fuzzy controller is simple, robust and obtained result are accurate.

In chapter, five a neural controller for mobile robot navigation, in the dynamic environments using the principle of back propagation algorithm has been discussed. The algorithm produces the robot's path positioned within the road boundaries and avoids any fixed as well as moving obstacles along the path. The algorithm also produced acceptable results when tested with different kinds of static as well as moving obstacles. The controllers found suitable control torques, permitting the robot to follow these paths. The significance of this work is the development of a dynamic system model and controllers for mobile robot navigation, rather than robot manipulators, which is a new research area. In addition, the navigation system can be utilised in numerous applications, including various defenses, industrial and medical robots. Simulation and experimental results verify the effectiveness of the developed navigation algorithm and the controllers.

In chapter six, adaptive neuro-fuzzy inference system (ANFIS) approach is analysed for robot navigation. In adaptive neuro-fuzzy modeling, there is a tendency to sacrifice model interpretability in pursuit of model accuracy. The main contribution is to overcome this problem by using takagi-sugano method to evaluate the similarity among fuzzy membership functions. Similar membership functions are then combined to minimise the number of linguistic terms. The result shows that it is possible to keep the fuzzy model concise and interpretable while maintaining a high level of model accuracy. A piece of software has been developed under windows environment to implement the adaptive neuro fuzzy controller for robot navigation (Appendix-A). The developed ANFIS controller has been compared with other approaches the result found to be satisfactory.

In chapter seven, heuristic rule base neural network (HRBN) controller has been developed. The output from the heuristic rule base is fed as an input (interim steering angle) to neural network and the final outputs (final steering angle) from the neural controller are used for motion and turning control of robots. The inputs to the heuristic rule base are obtained from the robot sensors (such as left, front, right obstacle distances and the target angle). The HRBN controller is used to avoid various shaped obstacles and to reach target. A Petri-net model has been developed and is used to take care of inter-robot-collision during multiple mobile robot navigation. By using the algorithm it has been visualised that, multiple mobile robots can navigate successfully avoiding static as well dynamic obstacles placed in the environment and reach the target successfully. Simulation software has been developed to test the proposed algorithms and loaded into the Khepera-III and Koala mobile robot to perform and validate experimental test. The developed methodology has been compared with the other approach proposed by many researchers, which shows a very good agreement.

The proposed research takes holistic approach to address the problem of extending the application domain. The holistic approach is applied to design the intelligent controller for mobile robot. Local navigation, by definition, cannot generate an optimal trajectory generally because no map information is available. The robot only knows where it is and where the goal is. Furthermore, the optimality of a global path, obtained by a concatenation of the local paths to be decided upon at each instant of time, can be only determined after the completion of navigation. The solution obtained from current research is the navigational path analysis of mobile robot in various environments. The results obtained from various approaches are given in Table 8.1. It shows the percentage of deviation of experimental results with respect to simulation result in various controllers being used for finding the navigational path and time taken to reach the target by mobile robot.

Table 8.1. Results deviation of travelled path and time taken during simulation and experimental mode

S.No.	Navigational Analysis with various Controller	Percentage of Results deviations Simulation Vs Experimental mode	
		Path	Time
1.	Navigation with Fuzzy controller	12.27%	12.26%
2.	Navigation with Neural controller	11.58%	11.59%
3.	Navigation with ANFIS controller	5.19%	14.15%
4.	Navigation with HRBN controller	5.12%	13.99%

A simulation comparison has been done between various techniques i.e. Fuzzy, Neural, ANFIS and HRBN controller (Fig. 8.1). During the comparison path length of “13.8 meter” and “8.3 meter”, time taken to reach the target “14.63 second” and “12.93 second” are recorded for fuzzy and ANFIS controllers respectively (Fig. 8.1(a)).

From Fig. 8.1(b) path length of “12.2 meter” and “6.6 meter”; time taken to reach the target “12.93 second” and “7.02 second” are observed for neural and ANFIS controllers respectively. Also during the comparison path length of “15.4 meter” and “9.6 meter”, time taken to reach the target “16.32 second” and “10.21 second” are recorded for fuzzy and ANFIS controllers respectively (Fig. 8.1(c)).

Path length of “6.6 meter” and “5.9 meter”; time taken to reach the target “7.02 second” and “6.25 second” are recorded respectively (Fig. 8.1(d)) for ANFIS and HRBN controllers during the comparison.

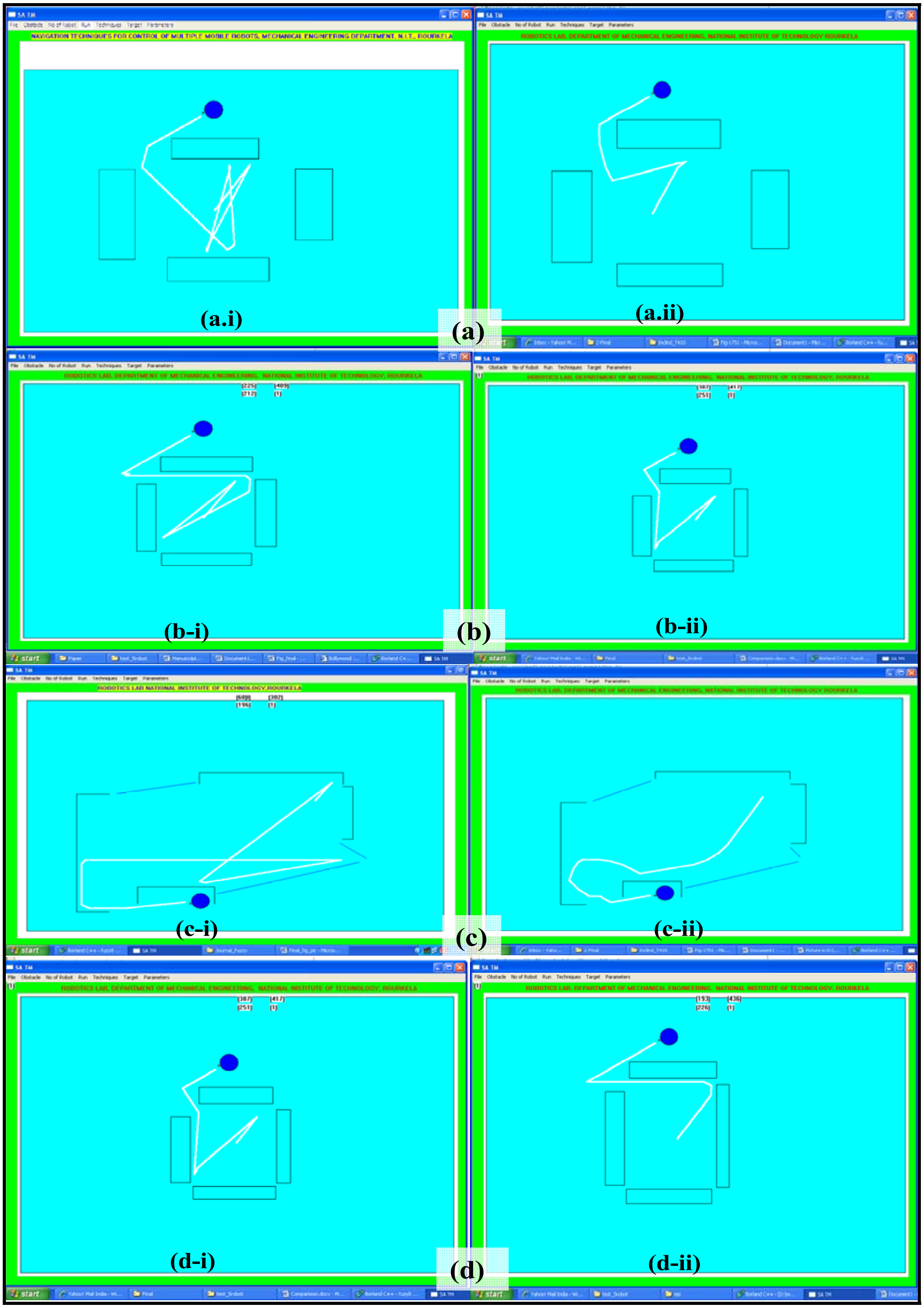


Figure 8.1. Comparison of results between Fuzzy, Neural, ANFIS and HRBN controller.

9 Conclusions and Future Works

The previous chapters have presented the background, approach and results of this research in detail. This chapter summarises the conclusions of the research and proposes idea for future work. This investigation expects to make the following contributions to the field of navigational path analysis of mobile robots in various environments.

9.1 Conclusions

In this research proposal, attempt has been made to solve a problem related to navigational path analysis of mobile robots in various environments. The above investigation has been carried out in several stages as follows:

1. Starting from the kinematics analysis a dynamic controller for a mobile robot is developed.
2. A fuzzy and neural network controller for navigating mobile are developed.
3. Further Adaptive Network based Fuzzy Inference System (ANFIS) controller for controlling multiple mobile robot is developed and finally Heuristic Rule Base Neural network controller (HRBNC) for mobile robot is developed.

The conclusions drawn from the above investigation are as follows:

1. From the kinematic analysis of mobile robot (chapter-3), left wheel and right wheel velocities of the mobile robot has been calculated. From the wheel velocities, steering angle for the robot is calculated. In this thesis, by using robust adaptive control technique, a dynamic controller for a mobile robot is proposed. The proposed dynamic controller can track the desired velocity, which is generated by kinematic controller, without exact knowledge about the dynamic model of a mobile robot.
2. In chapter four, a robust fuzzy controller has been developed for navigation of mobile robot in the presence of obstacles. The proposed membership function is found best for navigation of mobile robots in various environments.
3. A neural network controller has been developed for mobile robot navigation in chapter 5. It is found that the neural controller is better than the fuzzy controller in terms of position accuracy.

4. The neural network technique has been modified to produce an ANFIS controller and is discussed in chapter 6. A human perception based HRBN controller is analysed in chapter 7. Both the techniques are used for enhancing the navigational path analysis and planning performance of the robots.
5. The best performing controllers are based on the ANFIS control technique and the human perception based HRBN control technique, which has been found to yield equally robust navigation results. From the demonstrated results of path optamisation and inter collision avoidance among robots, it is noted that the ANFIS and perception based HRBN controller can be applied successfully in multi-robot cooperative exercises. The results of all the proposed techniques have been discussed in Chapter 8.

Validation of theoretical work has been done by simulation and a real world tests. A ROBNAV simulation software has been developed. Several mobile robots have been used in the tests: NITR, Khepera-II, Khepera-III and Koala.

9.2 Future Works

This work provides a foundation for future expansion of integrated designing approaches of intelligent controller based on artificial intelligence technique. Regardless of all research that has been conducted, autonomous navigation in various environments is still an open area of research. There are a number of interesting directions to pursue as future work. The suggestions with several crucial and promising researches for future investigation are as follow.

In the current research work, the techniques developed for navigational path analysis of mobile robot enable the robots to avoid collision among each other and with static obstacles. However, further development of the techniques may be required for the avoidance of moving obstacles other than the robots. This will make the algorithm more effective in dealing with unpredictable real life situations. The navigational techniques developed in this research work are capable of detecting and reaching the static targets. Further modifications in these navigational techniques may be carried out so that the robots can not only detect dynamic targets but also reach them using an optimum path. Further research is required for cooperative behaviour coordination between the robots for task and handling a particular object by avoiding static as well as moving obstacles.

Appendix-A

ROBNAV Software used for Navigation of Mobile Robot

The typical screen of 'ROBNAV' software has been developed using C++ shown in Fig. A.1. The software runs on operating under WINDOWS NT/95/ 98/2000/XP/Vista. The menus incorporated in the software are:

A.1. Obstacle Menu: The Obstacle Menu allows the user to draw different types of obstacles in the robots' environment. The shape of the obstacle has been shown in Fig. A.2.

A.2. Number of Robot Menu: Using this menu, a user can draw any number of robots (<=1000) as required to be placed in the environment. The number of robot has been shown in Fig. A.3(i).

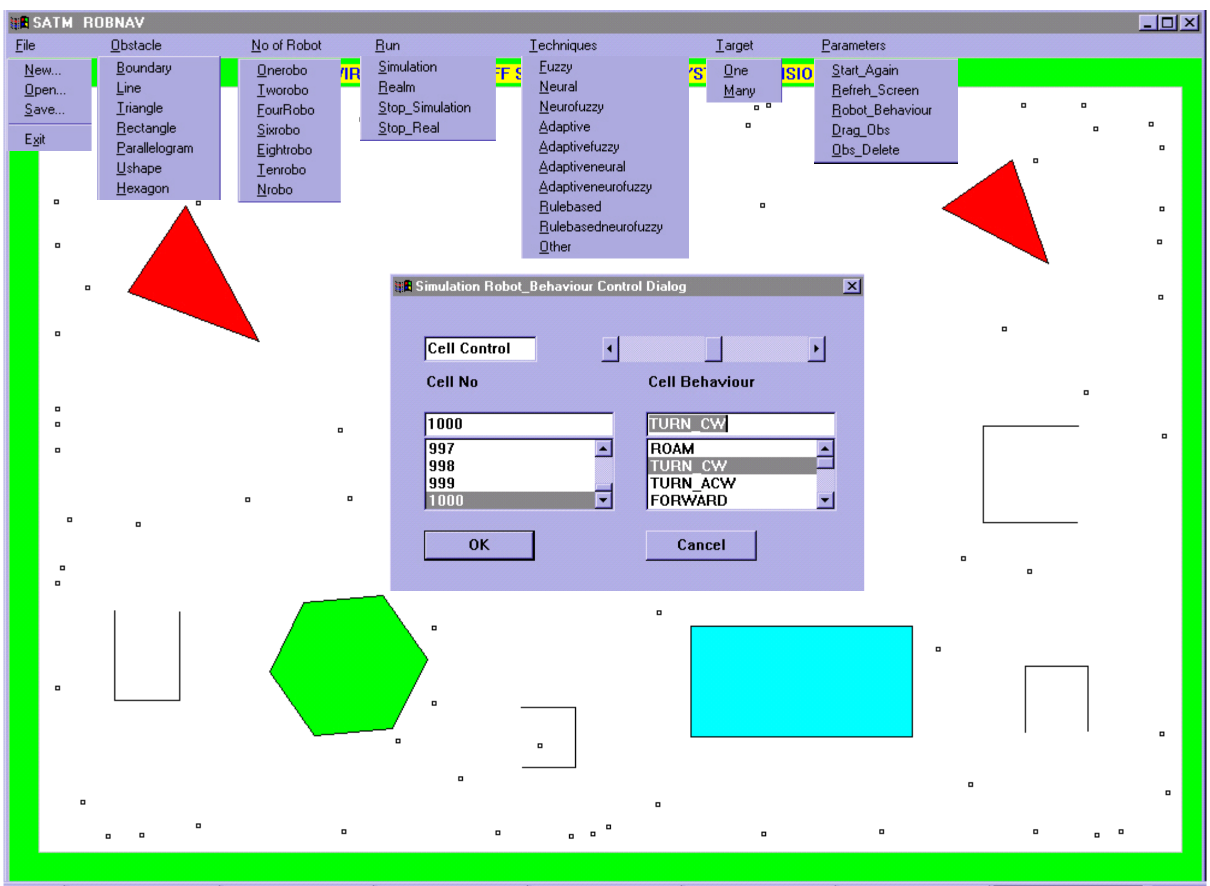


Figure A.1. The Typical Screen of ROBNAV Software used for Navigation of Mobile Robots.

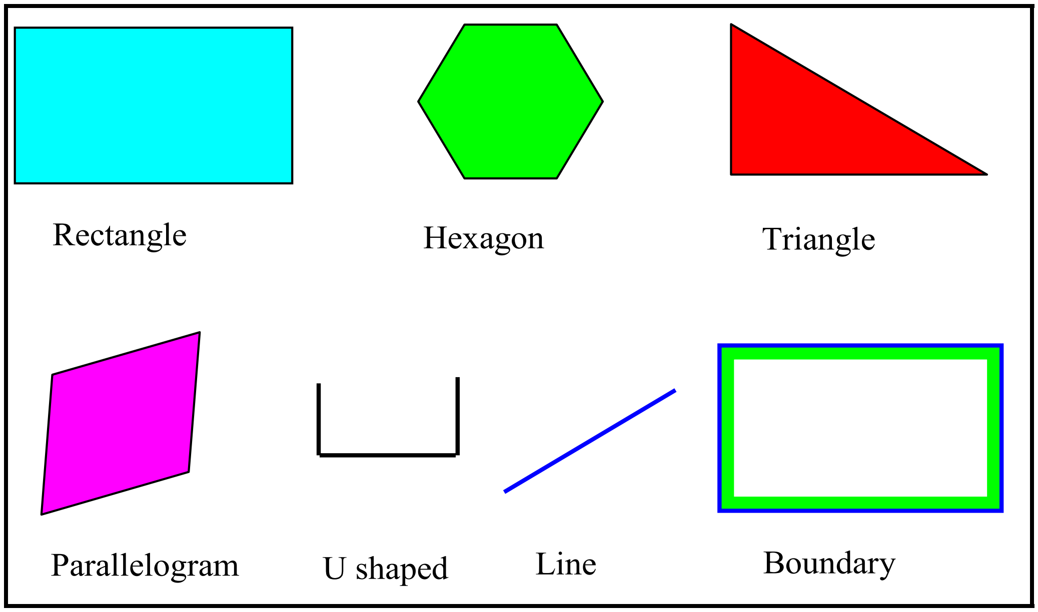


Figure A.2. The obstacles into the software.

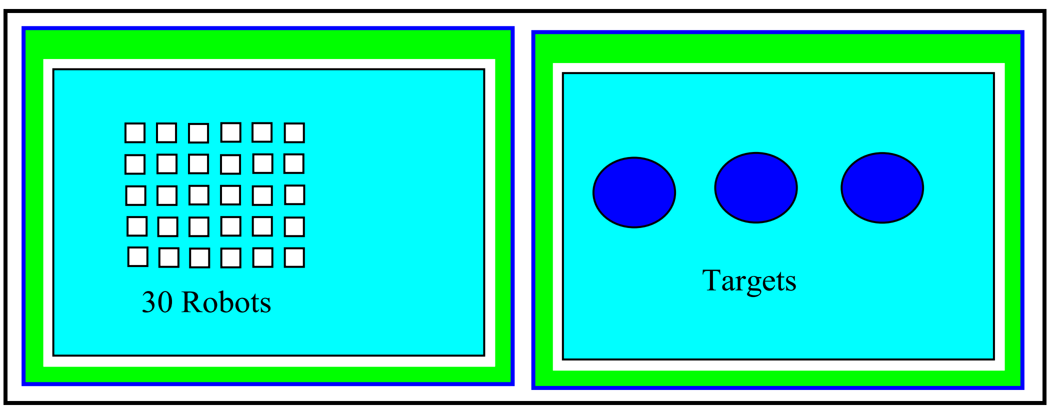


Figure A.3. (i) The number of robot into the software (ii) The target into the software.

A.3. Run Menu: With this menu, the user can choose to run the software in simulation mode or control the navigation of real mobile robots.

A.4. Techniques Menu: This menu enables the user to select the techniques to control the navigation of the robots.

A.5. Target Menu: This menu is for placing targets in the environment. The target has been shown in Fig. A.3 (ii).

A.6. Parameter Menu: This menu enables the user to start again a process, refresh the screen, robot behaviour to select a particular robot and control its movements manually, and drag any of the obstacles to any place in the environment, and obstacle delete from the environment.

Appendix-B

Petri Net Model (PNM)

The theory of Petri Nets was developed from the work of Carl Adam Petri in Germany in 1962. He developed a new model for information flow in a communication system [222]. Petri Net model is used as a visual communication aid to model the system behaviour. It is based on strong mathematical foundation. Petri Net is a graphical paradigm for the formal description of the logical interactions among parts or of the flow of activities in complex systems. Petri Net is particularly suited to model:

–Concurrency and conflict,

–Sequencing, conditional branching and looping,

–Synchronization,

–Sharing of limited resources and

–Mutual exclusion.

B.1. Basic Definitions of Petri Net Model

Petri net model (PNM) has been developed by Petri as a means of representing the behaviour of a dynamical system. The purpose of PNM is to specify the integration of the individual efforts on avoiding inter collision and to achieve co-operation between multiple robots.

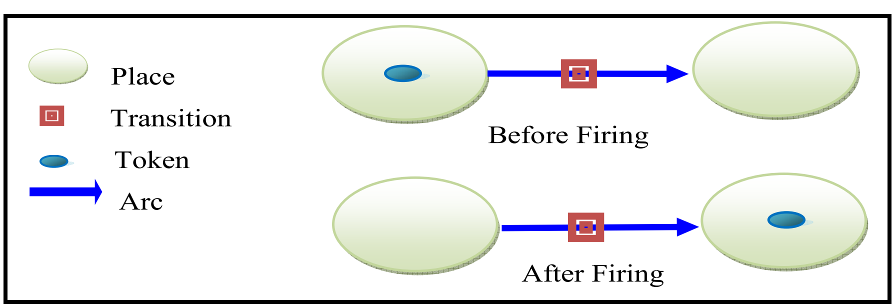


Figure B.1. A Simple Petri Net Model.

PNM can be used as a motion scheduler and it is capable of representing concurrent activities and the responsibility of decisions in the coordination level of the intelligent mobile robot navigation system. A Petri net is a bipartite directed graph consisting of two kinds of nodes: places and transitions [222] (Figure B.1).

- Places typically represent conditions within the system being modeled.
- Transitions represent events occurring in the system that may cause change in the condition of the system.
- Arcs connect places to transitions and transitions to places but never an arc from a place to a place or from a transition to a transition. In addition to the basic elements of petri nets i.e., places, transitions and direct arcs, tokens are included to model the systems. In petri net theory, places represent status such as operation process, conditions or availability of resources e.g., a robot is ready to move in an environment. Transitions are used to model events i.e., the start and termination of operations. Places contain tokens (denoted by circles) and the distribution of tokens in the place of petri net is called its marking. The execution of a Petri net is controlled by the position and movement of these tokens.

In a petri net model, petri net structure (PN) can be defined as a five tuple. The mathematical analysis of the PNM is defined by Eq. (b.1).

$$PN = < P, T, F, W, M_0 > \qquad \text{(b.1)}$$

Where:

$\mathrm{P} = \{\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3 \ldots \ldots .. \mathrm{P}_\mathrm{m}\}$ is a finite set of places.

$\mathrm{T} = \{\mathrm{t}_1, \mathrm{t}_2, \mathrm{t}_3 \ldots \ldots .. \mathrm{t}_\mathrm{n}\}$ is a finite set of transitions.

$\mathrm{F} \in (\mathrm{P} \times \mathrm{T}) \cup (\mathrm{T} \times \mathrm{P})$ is a set of curve.

W: F= {1, 2, 3..}is a weight function and w (n_s, n_d) denotes the weight of the edge from n_s to n_d.

M_0 : P = {0, 1, 2, 3 . . .} is the initial marking.

$P \cup T \neq 0$ and $P \cap T = 0$, Petri nets are used to model complex systems that can be described in terms of states and their changes.

Input arcs are directed arcs drawn from places to transitions, representing the conditions that need to be satisfied for the event to be activated as shown in Fig. B.2(i). Output arcs are directed arcs drawn from transitions to places, representing the conditions resulting from the occurrence of the event as shown in Fig. B.2(ii).

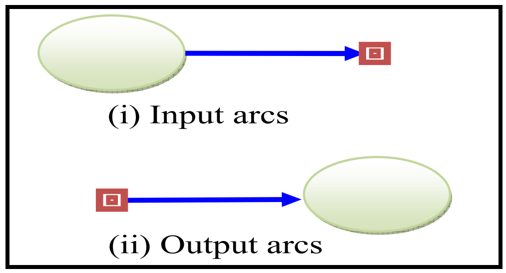


Figure B.2. The Input and Output arcs.

Input places of a transition are the set of places that are connected to the transition through input arcs where as the output places of a transition are the set of places to which output arcs exist from the transition as depicts in Fig.B.3.

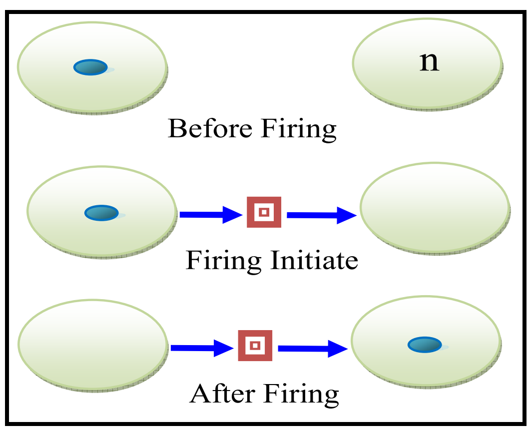
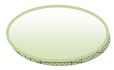


Figure B.3. Firing of Petri Net Model.

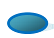
Tokens are dots (or integers) associated with places; A place containing tokens indicates that the corresponding condition holds. Marking of a petri net is a vector listing the number of tokens in each place of the net (n_1, n_2, n_3,......n_p), P = of places. When input places of a transition have the required number of tokens, the transition is enabled. An enabled transition may fire (event happens) taking a specified number of tokens from each input place and depositing a specified number of tokens in each of its output place as shown in Fig.B.3.

Role of a place 

- A type of communication medium, like a telephone line, a middleman, or a communication network.
- A buffer: for example, a depot, a queue or a post bins.
- A geographical location, like a place in a warehouse, office or hospital.
- A possible state or state condition: for example, the floor where an elevator is, or the condition that a specialist is available.

Role of a transition 

- An event: for example, starting an operation, the death of a patient, a change seasons or the switching of a traffic light from red to green.
- A transformation of an object, like adapting a product, updating a database, or updating a document.
- A transport of an object: for example, transporting goods, or sending a file.

Role of a token 

- A physical object, for example a product, a part, a drug, a person.
- An information object, for example a message, a signal, a report.
- A collection of objects, for example a truck with products, a warehouse with parts, or an address file.
- An indicator of a state, for example the indicator of the state in which a process is, or the state of an object.
- An indicator of a condition: the presence of a token indicates whether a certain condition is fulfilled.

Appendix-C

Robots Hardware used for Experimental Verification

C.1 NITR Mobile Robot

The NITR mobile robot developed in the robotics laboratory has been shown in Fig. C.1 used for experimental results. It has two differentials drive standard wheels and two supported ball wheels front and rear of the robot used for stability. The standard driving wheels have a radius of 35mm and are mounted on an axle of length 180 mm. The chassis of the robot measures 160 $\times 180\times 150$ mm (L$\times$W$\times$H) and contains two DC gear servo motors for driving the wheels. Five pairs of infrared sensors are connected for obstacle detection. The radio modem used for radio frequency transmission, and 12-V battery is used for power supply. The wheels are driven by motors having rated torque 12 Kg-cm at 30 rpm and at 12 rated voltage.

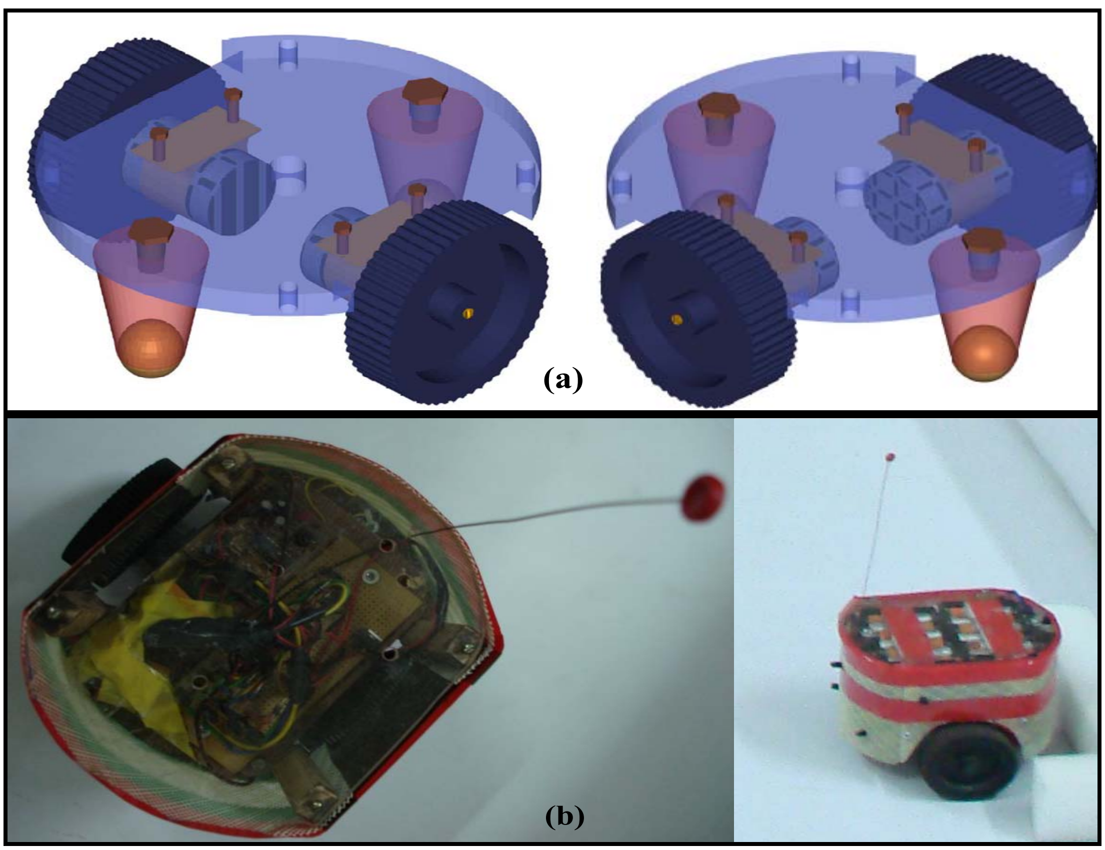


Figure C.1. (a) Chassis of the robot (b) Working model of NITR Mobile Robot.

C.2 Khepera-II Mobile Robot

The Khepera-II mobile robot has been illustrated in Fig. C.2. The active control mode is set according to the kind of command received. If the controller receives a speed control command, it switches to the speed mode. Different control parameters can be set for each of the two control modes. This sensor device allows two measures: The normal ambient light. This measure is made using only the receiver part of the device, without emitting light with the emitter. A new measurement is made every 20 ms. During the 20 ms, the sensors are read in a sequential way every 2.5 ms. The value returned at a given time is the result of the last measurement made. The output of each measurement is an analogue value converted to a 10 bit digital value. The Khepera is equipped with four Nickel Metal Hydride batteries providing 250mAh each. The serial communication protocol is designed to control all Khepera's functions using a RS232 serial line. The control protocol is used to send control messages to the robot. The Khepera robot is equipped with two DC motors and incremental encoders. An easy and efficient way to control DC motors is to use a Pulse Width Modulation signal. The Khepera's API provides two controllers, one for position control and the other for speed control.

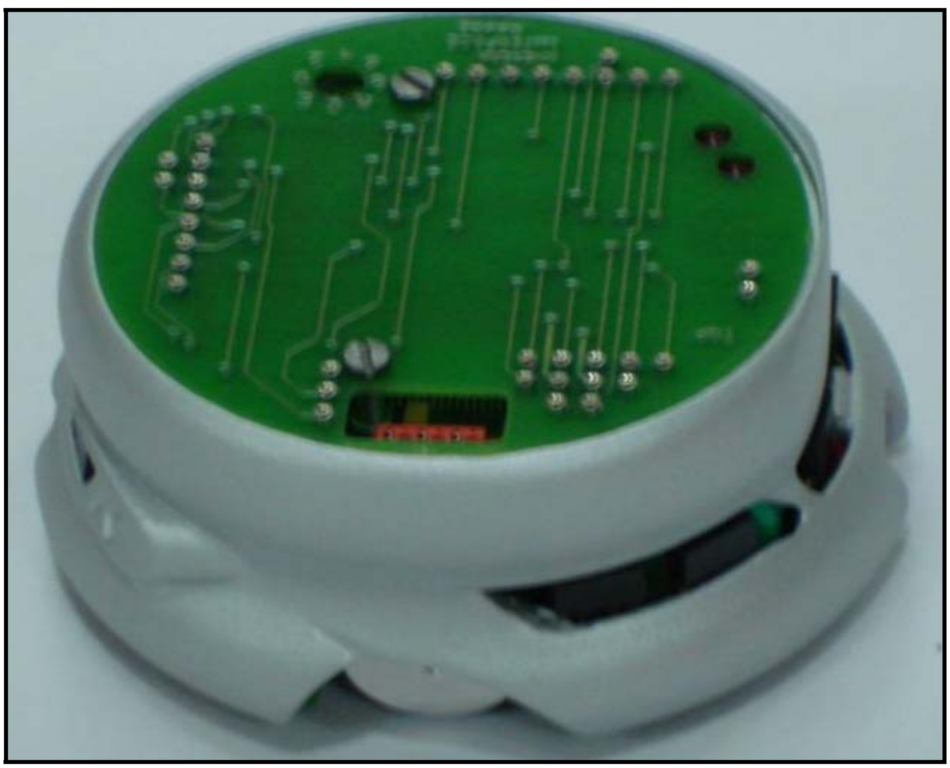


Figure C.2. KHEPERA-II mobile robot.

C.3 Khepera-III Mobile Robot

The Khepera-III mobile robot has two driving wheels and a point supporter for stability. Each wheel is moved by a DC motor coupled with the wheel through a 43.2:1 reduction. The motor has its own embedded incremental encoder, placed on the motor axis, gives 16 pulses per revolution of the motor. Each motor is driven by its own motor controller implemented in a PIC18F4431. The motor controller can be used in two control modes, the speed or position mode. The active control mode is set according to the kind of command received. It has nine sensors placed around the robot and two placed on the bottom. The later allow experiments like line following. These sensors embed an infra-red light emitter and a receiver. In its base set, five sensors are placed around the robot and are positioned and numbered as shown in Fig. C.3. Five sensors are in fact five pairs of ultrasonic devices where each pair is composed of one transmitter and one receiver. The ultrasonic sensors are powered by a 20 Vdc source. When the upper body is mounted, there's some noise because of inside rebound echo, which are deleted in software. It has equipped with a battery pack composed of two Li-Ion Polymer elements. This provides a 7.4V volt battery with a 1400 mAH capacity. The communication interface module used a standard RS232 line, while the interface module converts RS232 signal into a TTL level signal to communicate with the robot.

Figure C.3. KHEPERA-III mobile robot.

C.4 Koala Mobile Robot

The Koala robot is a robotic platform for real world experiments and is more powerful, and capable of carrying larger accessories than Khepera shown in Fig. C.4. It rides on six wheels having 320 × 320 × 200 mm (L×W× H), and sports stylish bodywork for attractive demonstrations. Every wheel is moved by a DC motor coupled with the wheel through an 84:1 reduction gear. An incremental encoder is placed on the motor axis and gives 100 pulses per revolution of the motor. This allows a resolution of 8400 pulses per revolution of the wheel that corresponds to 32.5 pulses per millimeter of forward displacement of the robot. Its weight is 4.0kg with battery and 3.6 kg without battery. The Koala main processor has the direct control on the motor power supply and can read the pulses of the incremental encoder using a special unit called UPP (Universal Pulse Processor). It can also read the current used by each motor, which are proportional to the torque on the wheels. The processor installed in the koala robot is Motorola 68331 @ 22MHz, RAM is 1Mbyte and ROM is 1Mbyte. The sensors mounted on the robot are sixteen Infrared proximity and ambient light sensors, four optional triangulation longerrange IR sensors and six optional ultrasonic sonar sensors. The maximum payload the robot can take is 3 kg. It has been designed for easy to use, easy to transport, and able to deal with a standard office environment as well as a rough indoor terrain. It is also fully software compatible with Khepera.

Figure C.4. Koala mobile robot.

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Mr. Mukesh Kumar Singh is a faculty member in the Department of Mechanical Engineering, Government Engineering College Bilaspur-09, Chhattisgarh, India. He has 14 years of research and teaching experience in his field. He did M.Tech. in CAD/CAM. This dissertation is submitting for fulfillment of the Ph.D. degree. The contact address is:

Mukesh Kumar Singh
Department of Mechanical Engineering
Government Engineering College Bilaspur.
Phone: 07752-260526 (o) Fax: 07752-260339(o).
C/3, Government Engineering College Campus
Koni, Bilaspur, Chhattisgarh, India- 495009. +919479171019(cell).
E-mail: mukesh3003@yahoo.co.in, mukesh3003@gmail.com

Navigational strategies of mobile robots: a review

Dayal R. Parhi*

Department of Mechanical Engineering,
NIT Rourkela,
Orissa 769008, India
Email: dayalparhi@yahoo.com
*Corresponding author

Mukesh Kumar Singh

Department of Mechanical Engineering,
Government Engineering College,
Bilaspur, Chattisgarh 495009, India
Email: mukesh3003@yahoo.co.in

Abstract: Present research and development in the area of mobile robots mainly aims at study of various techniques, methods and sensors being used for navigation of mobile robots. Different techniques have been discussed for the navigation of mobile robots in the first part. These techniques can be subdivided as (1) fuzzy logic technique, (2) neural network technique and (3) genetic algorithm technique. In the second part, five methods are being discussed for navigation of mobile robots. These methods are (1) potential field method, (2) grid-type method, (3) heuristic method, (4) adaptive navigation method and (v) Virtual Impedance method. The last segment focuses on different sensors being used for navigation of mobile robots. The sensors discussed are (1) ultrasonic sensor, (2) laser sensor, (3) magnetic compass disk sensor, (4) infrared sensor and (5) vision (camera) sensor. Keeping the above strategies in forefront, a comprehensive discussion has been made and is described methodologically in the current paper.

Keywords: fuzzy logic; neural network; GA; genetic algorithm; sensors; navigation; mobile robots.

Reference to this paper should be made as follows: Parhi, D.R. and Singh, M.K. (2009) 'Navigational strategies of mobile robots: a review', *Int. J. Automation and Control*, Vol. 3, Nos. 2/3, pp.114–134.

Biographical notes: Dayal R. Parhi received his first PhD in Mobile Robotics from Cardiff School of Engineering, UK, and second PhD in Vibration Analysis of Cracked Structures from Sambalpur University, Orissa, India. He has 16 years of research and teaching experience in his fields. Presently, he is engaged in mobile robot navigation research, and a faculty member in the Department of Mechanical Engineering, National Institute of Technology Rourkela, Orissa, India.

Mukesh Kumar Singh is a faculty member in the department of Mechanical Engineering, Government Engineering College, Bilaspur, Chhattisgarh, India. He has 12 years of research and teaching experience in his field. He did MTech in CAD/CAM. Presently, he is doing research for his PhD in the field of mobile robots navigation.

Intelligent fuzzy interface technique for the control of an autonomous mobile robot

D R Parhi[1]* and **M K Singh**[2]
[1]Department of Mechanical Engineering, NIT Rourkela, Orissa, India
[2]Department of Mechanical Engineering, GEC Bilaspur, Chattisgarph, India

The manuscript was received on 28 January 2007 and was accepted after revision for publication on 27 May 2008.

DOI: 10.1243/09544062JMES955

Abstract: In this article, research has been carried out on the control technique of an autonomous mobile robot to navigate in a real-world environment, avoiding structured and unstructured obstacles, especially in a crowded and unpredictably changing environment. Here a successful way of structuring the navigation task, dealing with the issues of individual robot behaviours, is discussed. Action coordination of the behaviours has been addressed using fuzzy logic in the present research. The inputs to the proposed fuzzy-control scheme consist of a heading angle between a robot and a specified target, and the distances between the robot and the obstacles to the left, front, and right of its locations, being acquired by an array of sensors. The proposed intelligent controller for mobile robot navigation algorithm employing fuzzy theory has been applied in a complex environment. The results are verified in simulation and experimental modes, which are in good agreement.

Keywords: navigation, dynamic environment, fuzzy logic, autonomous robots

1 INTRODUCTION

Intelligent control of a mobile robot is one of the challenging tasks among the researchers and scientists throughout the world. Therefore, the current research and development of mobile robots have attracted the attention of researchers in the areas of engineering, computer science, biology, mining, and others. This is due to the high application potential of mobile robots. Autonomous mobile robots are intelligent agents that can perform desired tasks in unstructured environments without continuous human guidance [**1**–**4**]. Many kinds of robots are autonomous to some degree. One important area of current robotics research is to enable the robot to cope with its environment whether this is on land, underwater, in the air, underground, or in space. A fully autonomous robot in the real world has the ability to:

(a) gain information about the environment;
(b) travel from one point to another point, without human navigation assistance;
(c) avoid situations that are harmful to people, property, or itself;
(d) repair itself without outside assistance.

A robot may also be able to learn autonomously. Autonomous learning includes the ability to:

(a) learn or gain new capabilities without outside assistance;
(b) adjust strategies based on the surroundings;
(c) adapt to surroundings without outside assistance.

Navigation for mobile robots can be well-defined in mathematical (geometrical) terms. It also involves many distinct sensory inputs and computational processes. Elementary decisions such as turn left, or turn right, or run or stop are made on the basis of thousands of incoming signals [**5**–**7**]. Thus, it is necessary to define what navigation is and what the function of a navigation system is. Navigation is traditionally defined as the process of determining and maintaining

**Corresponding author: Department of Mechanical Engineering, NIT Rourkela, C/14, NIT Campus, Rourkela, Orissa 769008, India. email: dayalparhi@yahoo.com*

Real-time navigational control of mobile robots using an artificial neural network

D R Parhi[1]* and **M K Singh**[2]

[1]Department of Mechanical Engineering, National Institute of Technology Rourkela, Orissa, India

[2]Department of Mechanical Engineering, Government Engineering College Bilaspur, Chhattisgarh, India

The manuscript was received on 27 October 2008 and was accepted after revision for publication on 5 January 2009.

DOI: 10.1243/09544062JMES1410

Abstract: This article deals with the reactive control of an autonomous robot, which moves safely in a crowded real-world unknown environment and reaches a specified target by avoiding static as well as dynamic obstacles. The inputs to the proposed neural controller consist of left, right, and front obstacle distance to its locations and the target angle between a robot and a specified target acquired by an array of sensors. A four-layer neural network has been used to design and develop the neural controller to solve the path and time optimization problem of mobile robots, which deals with cognitive tasks such as learning, adaptation, generalization, and optimization. The back-propagation method is used to train the network. This article analyses the kinematical modelling of mobile robots as well as the design of control systems for the autonomous motion of the robot. Training of the neural net and control performances analysis were carried out in a real experimental set-up. The simulation results are compared with the experimental results and they show very good agreement.

Keywords: evolutionary robotics, artificial neural network, mobile robot, behavioural robotics

1 INTRODUCTION

There is significant interest in autonomous mobile robots, which may be defined as vehicles that are capable of intelligent autonomous navigation. Over the last decade, a great deal of research has reported on machine learning and how it has been applied to help mobile robots optimize their operational capabilities. One of the most important issues in the design and development of an intelligent mobile system is the navigation problem. This consists of the ability of a mobile robot to plan and execute collision-free motions within its environment. However, this environment may be imprecise, vast, dynamical, and either partially structured or non-structured. Robots must be able to understand the structure of this environment [**1**–**5**]. To reach their targets without colliding, robots must be endowed with perception, data processing, recognition, learning, reasoning, interpreting, and decision-making and action capacities.

Service robotics today require synthesizing robust automatic systems able to cope with a complex and dynamic environment [**6**]. To demonstrate this kind of autonomy Muñiz *et al.* [**7**] introduced a neural controller for a mobile robot that learns both forward and inverse odometry of a differential drive robot through unsupervised learning. They introduced an obstacle-avoidance module that is integrated into a neural controller. However, generally, the evolved neural controllers could be fragile in inexperienced environments, especially in real worlds, because the evolutionary optimization processes are executed in idealized simulators. This is known as the gap problem between simulated and real worlds. To overcome this, Kondo [**8**] focused on an evolving on-line learning ability instead of weight parameters in a simulated environment. Based on this, a neuromodulatory neural network model was proposed by them and is utilized as a mobile robot controller. Corradini *et al.* [**9**] used a neural network approach for the solution of the tracking problem of mobile robots. Racz and Dubrawski [**10**] presented a neural network-based approach for mobile robot localization in front of a certain local object. Yang and Meng [**11**] proposed a biologically inspired neural network approach for

**Corresponding author: Department of Mechanical Engineering, NIT Rourkela, C/14, NIT Campus, Rourkela, Orissa 769008, India. email: dayalparhi@yahoo.com*

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International Journal of Systems Science - Decision on Manuscript ID TSYS-2008-0440.R1

Thursday, 29 October, 2009 6:14 PM

From: "r.ashton@shef.ac.uk" <r.ashton@shef.ac.uk>

To: mukesh3003@yahoo.co.in

29-Oct-2009

Dear Mr. Singh:

I am pleased to advise you that your manuscript entitled "Path optimisation of mobile robot using artificial neural network (ANN) controller" which you submitted to International Journal of Systems Science has been found acceptable for publication.

Please send the final version of your files to the International Journal of Systems Science Editorial Office at r.ashton@sheffield.ac.uk.

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Reviewer(s)' Comments to Author:

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Fw: Decision on JEM1736R3 Tuesday, 3 November, 2009 11:46 AM

From: "dayal parhi" <dayalparhi@yahoo.com>

To: "Mukesh Singh" <mukesh3003@yahoo.co.in>

--- On Mon, 11/2/09, Journal of Engineering Manufacture
<jengmanuf@pepublishing.com> wrote:

\> From: Journal of Engineering Manufacture
<jengmanuf@pepublishing.com>
\> Subject: Decision on JEM1736R3
\> To: dayalparhi@yahoo.com
\> Date: Monday, November 2, 2009, 4:33 AM
\> 02 Nov 2009
\>
\> Ref: JEM1736R3
\>
\> Dear Dayal
\>
\> TITLE: Heuristic rule base hybrid neural network for
\> navigation of mobile robot
\> AUTHOR(S): Dayal R. Parhi, Ph.D.; Mukesh K Singh, M.Tech
\> (CAD/CAM)
\>
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\> Reviewer #2: The authors have revised the paper
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Re: Decision on JMES1751R1   Wednesday, 14 October, 2009 5:58 PM

From: "dayal parhi" <dayalparhi@yahoo.com>

To: "Journal of Mechanical Engineering Science" <jmechengsci@pepublishing.com>

Dear Rebecca and Sarah,

Thank you very much for the response and news!

Best regards.

Sincerely,

Dayal

--- On Wed, 10/14/09, Journal of Mechanical Engineering Science <jmechengsci@pepublishing.com> wrote:

> From: Journal of Mechanical Engineering Science <jmechengsci@pepublishing.com>
> Subject: Decision on JMES1751R1
> To: dayalparhi@yahoo.com
> Date: Wednesday, October 14, 2009, 4:09 AM
> Ref: JMES1751R1
>
> Dear Dayal
>
> TITLE: Navigational path analysis of mobile robots using
> ANFIS controller in dynamic environment
> AUTHOR(S): Dayal R. Parhi, Ph.D.; Mukesh K Singh, M.
> Tech(CAD/CAM)
>
> I am pleased to tell you that your work has now been
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Paper Status - Paper 206-3207

Tuesday, 17 February, 2009 5:47 AM

From: "journals@actapress.com" <journals@actapress.com>

To: mukesh3003@yahoo.co.in

Re: Paper Number 206-3207
Dear Mr. Mukesh Singh,

I am pleased to inform you that the above-mentioned paper, entitled "FUZZY CONTROLLER FOR PATH ANALYSIS AND PLANNING OF MOBILE ROBOT", has been provisionally accepted for publication in the International Journal of Robotics and Automation, providing you incorporate the reviewer's suggestions in your paper. Please access our online system to view the reviewer comments.

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